Cyclical Worker Flows: Cleansing vs. Sullying

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Abstract

Do recessions speed up or impede productivity-enhancing reallocation? To investigate this question, we use U.S. linked employer-employee data to examine how worker flows contribute to productivity growth over the business cycle. We find that in expansions high-productivity firms grow faster primarily by hiring workers away from lower-productivity firms. The rate at which job-to-job flows move workers up the productivity ladder is highly procyclical. Productivity growth slows during recessions when this job ladder collapses. In contrast, flows into nonemployment from low productivity firms disproportionately increase in recessions, which leads to an increase in productivity growth. We thus find evidence of both sullying and cleansing effects of recessions, but the timing of these effects differs. The cleansing effect dominates early in downturns but the sullying effect lingers well into the economic recovery.

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1 Introduction

Economists have long sought to understand how business cycles affect the reallocation of resources. Do recessions promote economic efficiency by "cleansing" out less productive firms and redirecting labor to more productive uses? Or, does the decline in job mobility in recessions "sully" productivity-enhancing worker reallocation, leaving workers matched to mediocre firms? In this paper we use U.S. linked employer-employee data to decompose the employment growth of high- and low-productivity firms into two components: growth accounted for by job-to-job moves and growth accounted for by flows through nonemployment. We find that job-to-job flows move workers from less productive to more productive firms and the rate at which workers move up this job ladder is highly procyclical. In contrast, less productive firms rely heavily on hiring jobless individuals in expansions and are disproportionately more likely to displace workers back to nonemployment in contractions. In this way, worker flows through nonemployment shift workers away from low-productivity firms in contractions.

We thus find empirical evidence of both cleansing and sullying effects of recessions, which feature in many models of the labor market. Much of the theoretical literature focuses on either cleansing or sullying effects. Schumpeter (1939) originally proposed that recessions may be productivity enhancing, driving out less productive uses of capital and labor and freeing these resources for more efficient use. The notion of cleansing effects of recessions was later revived in Davis and Haltiwanger (1990), Caballero and Hammour (1994), and Mortensen and Pissarides (1994).[1] Barlevy (2002) notes that cleansing effects of recessions appear at odds with observed procyclical job quality. He proposes a model whereby declines in job-to-job moves cause a drag on productivity in recessions, a sullying effect. Sullying effects of recessions feature more recently in a set of papers by Moscarini and Postel-Vinay (2013, 2016) (MPV). The MPV framework in particular yields a rich set of predictions for the cyclical reallocation of workers across the firm productivity distribution that we largely confirm in our empirical analysis.[2] More recent research by Lise and Robin (2017) and Baley,

[1]Unlike Schumpeter, the more recent literature does not argue that recessions are desireable but rather that, conditional on the adverse shock occurring, there may be an acceleration of the ongoing reallocation of resources to more productive uses in recessions.

[2]The MPV model builds on the job ladder framework of Burdett and Mortensen (1998) but importantly

Figueiredo, and Ulbricht (2020) use models with heterogeneity of both workers and firms that induce cyclical variation in sorting over the cycle. Within their frameworks, both of these papers suggest that the cleansing effect dominates the sullying effect.[3] Our empirical results suggest that the cleansing effects dominate at the start of a recession but that the sullying effects continue long into the economic recovery.

In our empirical analysis, we classify firms into high- and low-productivity firms based upon the relative ranking of firms in the measured distribution of firm-level productivity. We find that high-productivity firms grow faster: the differential growth rate averages 0.20 percent of employment on a quarterly basis. Decomposing the growth rate differential into the components due to job-to-job moves versus worker flows through nonemployment, we find that the propensity of high-productivity firms to grow faster is driven by their advantage in poaching workers from less productive firms. This advantage is large: the difference in the growth rates due to job-to-job moves is 0.61 percent per quarter. Low-productivity firms actually lose workers on net through poaching, and so hire relatively more jobless workers to sustain growth: the differential employment growth rate from worker flows through nonemployment (relative to high-productivity firms) is 0.41 percent per quarter.

We find that these patterns of worker reallocation between low- and high-productivity firms differ dramatically over the course of the business cycle. In expansions, high-productivity firms actively poach workers from less productive employers. During recessions, this job ladder collapses yielding a sullying effect. The nonemployment margin also changes dramatically across the cycle. In expansions, low-productivity firms

for our purposes incorporates business cycle dynamics. In their framework, search frictions prevent workers from immediately moving into desirable job matches and workers move to better firm matches via job-to-job flows. High-productivity firms are able to offer higher wages and thus are able to grow faster in expansions than less-productive firms, who must rely on the pool of unemployed workers in filling vacancies. In recessions, this cyclical job ladder collapses, yielding a sullying effect. Our empirical results are largely consistent with these predicted dynamics. Our results build on the findings in Haltiwanger, Hyatt, Kahn, and McEntarfer (2018) and Haltiwanger, Hyatt, and McEntarfer (2018). This earlier work provides support for a procyclical job ladder in terms of firm earnings and productivity. The current paper is distinguished by explicitly considering the sullying and cleansing contributions of flows through the lens of the impact on the share of employment at high and low productivity firms. This earlier work does not explore decompositions of productivity growth into cleansing and sullying components. Bertheau, Bunzel, and Vejlin (2020) report broadly similar patterns on poaching by high-paying and low-paying firms using Danish data.

[3] However, worker flows across firms ranked by firm productivity are not targeted directly when they estimate their models. While we do not explicitly consider worker heterogeneity in our empirical analysis, we do provide novel evidence on the patterns of worker flows across firms ranked by productivity that are relevant for these models of sorting.

grow primarily through hiring jobless workers. In contractions, worker separations to nonemployment from low-productivity firms spike disproportionately and hires from nonemployment into low-productivity firms decline disproportionately. This cleansing effect peaks earlier in a downturn compared to the collapse of the job ladder that lingers into the early stages of a recovery. Cleansing effects are stronger than sullying effects when the unemployment rate surges during recessions, but they are almost completely absent in the times of high unemployment that follow recessions.

What are the implications of these business cycle dynamics on aggregate productivity growth? To answer this question we use an accounting decomposition of an index of aggregate productivity growth that is the employment-weighted average of a firm-level measure of productivity, which is measured in logs. On average, worker reallocation through job-to-job flows contributes 0.1 log points to the index of overall productivity growth each quarter. This is a substantial contribution to the average quarterly rate of aggregate productivity growth, which is 0.33 based on our data. However, during recessions there is clear evidence of a sullying effect. This is particularly true during the Great Recession. Prior to the recession, in 2006:1, worker reallocation via job-to-job flows contributed 0.13 log points to quarterly aggregate productivity growth but this contribution declined to 0.02 by 2009:2. Acting against this is a cleansing effect that operates via worker flows through nonemployment. In 2006:1, worker reallocation via nonemployment contributed -0.1 log points to quarterly aggregate productivity growth but this increased to 0.08 in 2009:1. We show that the during periods of rising unemployment the cleansing impact on productivity outweighs the sullying impact. However, during periods when unemployment is above trend the sullying impact on productivity outweighs the cleansing impact.

Our primary analysis uses revenue per worker to measure relative productivity within the firm's industry. This has the advantage of allowing us to measure productivity within most industry sectors, but has two key disadvantages.[4] First, we cannot easily compare productivity across sectors and so our main analysis abstracts from productivity-enhancing reallocation from less to more productive sectors. Second, revenue per worker reflects both

[4]Total factor productivity measures are available for only handful of sectors that are a shrinking share of the U.S. economy.

"innate" firm productivity as well as sorting of workers across firms. We assess these issues using the AKM decomposition of earnings.[5] The AKM firm fixed effect represents the pay-premium workers receive independent of worker quality and while not a direct measure of productivity, canonical models suggest that the relative ranking should be highly correlated with productivity differences within and across industries. We find that the cyclical patterns of hires and separations via poaching and nonemployment are very similar whether we rank firms based on revenue per worker of the AKM firm fixed effect. Thus, our results do not appear to be driven by cyclical sorting of worker types across firms.[6]

Finally, we consider the implications of the worker flows across firms ranked by productivity for worker earnings. We find that worker movements from low- to high-productivity firms move workers into higher-paying firms, as measured by both firm average earnings and the AKM firm fixed effect. These earnings changes move strongly with their productivity analogues but are roughly half of the magnitude. Thus, workers obtain a substantial fraction of the gains from movements onto and up the firm productivity job ladder, but there is suggestive evidence of incomplete pass-through of gains to workers.

The paper proceeds as follows. Section 2 describes the data. Section 3 presents evidence on worker movements onto, up, and off of the firm productivity job ladder over the cycle. Section 4 quantifies the implications of the cyclical worker flows for cyclical variation in productivity. Section 5 discusses implications for earnings. Section 6 concludes.

2 Data

A key contribution of our paper is the matching of U.S. Census Bureau linked employer-employee data to new productivity measures also developed at Census. We will first describe the linked employer-employee data, and how we use it to decompose firm growth via job-to-job moves versus flows through nonemployment. The Longitudinal Employer-Household Dynamics (LEHD) data contain quarterly earnings records collected by state unemployment

[5]AKM refers to the decomposition developed by Abowd, Kramarz, and Margolis (1999).

[6]Haltiwanger, Hyatt, and McEntarfer (2018) and Crane, Hyatt, and Murray (2020) examine cyclical sorting of heterogeneous workers across heterogeneous firms. Both papers find evidence that the assortative matching of workers and firms is countercyclical: a greater share of low-productivity workers are able to match to better firms in expansions.

insurance (UI) programs, linked to establishment-level data from the Quarterly Census of Employment and Wages (QCEW). LEHD employment coverage is quite broad, covering over 95 percent of private sector workers and almost all state and local government employment.[7] State-level data availability varies by year, as states began sharing UI and QCEW data with the Census Bureau at different times. In this paper we use LEHD data for private-sector employers in 28 states from 1998-2015.[8] Our 28 states include many of the largest states so that our sample accounts for 65 percent of U.S. private sector employment.

The LEHD data allow us to decompose firm employment growth by worker hires and separations. We use the decomposition developed in Haltiwanger, Hyatt, and McEntarfer (2018) (HHM) and Haltiwanger, Hyatt, Kahn, and McEntarfer (2018) (HHKM) that yields an exact decomposition of firm employment growth due to workers switching jobs (what we call net job-to-job or net poaching flows) and growth due to flows between employment and nonemployment (what we call net nonemployment flows). A challenge for the identification of job-to-job flows in the LEHD data is that the data do not provide information on why a worker left one job and began another. We only have quarterly earnings, from which we infer approximately when workers left and began jobs. HHM and HHKM develop three alternative measures of job-to-job flows, and demonstrate that key findings on the nature of job ladders are robust to different approaches for identifying job-to-job moves in the LEHD data. We use the within/adjacent approach from HHM in this paper. This approach defines job-to-job transitions as those where the new job begins in the same or following quarter as the job separation. Based upon the robustness analysis in HHM, we are confident our main results are not sensitive to the specific rules we use amongst the set of rules they considered.[9]

To measure firm productivity, we use a relatively new firm-level database on productivity from Haltiwanger et al. (2017) based on the revenue and employment data from the Census

[7] For a full description of the LEHD data, see Abowd et al. (2009).

[8] Our 28 states are CA, FL, GA ,HI, ID, IL, IN, KS, ME, MD, MN, MO, MT, NC, NJ, ND, NM, NV, PA, OR, RI, SC, SD, TN, VA, WA, and WV. While we restrict our analysis to employers located in our 28-state sample, we use the complete set of available states to construct worker job histories. As described later in this section, our productivity measures reflect the labor productivity of the national firm.

[9] They also consider job-to-job flows restricted to those where the transition occurs within the same quarter and those with minimum disruptions in earnings. They find results that are very robust across these alternatives. Each of the different measures is highly correlated with the alternatives (pairwise correlations of about 0.98) and each of the LEHD based job-to-job flow series has a correlation of about 0.96 with CPS based job-to-job flows.

Business Register and the Longitudinal Business Database (LBD). Since the underlying revenue and employment data are from the Census Business Register, this database offers much wider coverage of labor productivity at the firm level than earlier studies that focused on sectors like manufacturing or retail trade. These data allow us to measure the log of real revenue per employee on an annual basis for a wide coverage of the private, non-farm, for-profit firms. Revenue is deflated with the Gross Domestic Product price deflator. This measure of productivity is a standard gross output per worker measure of productivity that is commonly used to measure productivity at the micro and macro level but is a relatively crude measure compared to using total factor productivity (TFP). However, in the empirical literature, this revenue labor productivity measure has been shown to be highly correlated with TFP based measures of productivity across businesses within industries. That is, within detailed industry year cells, Foster, Haltiwanger, and Krizan (2001) and Foster, Haltiwanger, and Syverson (2008) find that the correlation between TFP and gross output (revenue) per worker across businesses is about 0.6 within industries in the manufacturing sector. This finding is consistent with the implications of models with labor market adjustment frictions which motivate our analysis.[10] In our analysis below, we use this revenue labor productivity measure deviated from industry by year means.

The gross output per worker data while offering much wider coverage than earlier studies has some limitations. The data only cover about 80 percent of firms in the Census LBD. The latter cover all firms with at least one paid employee in the private, non-farm sector. One reason is that the revenue data are not available for non-profits. For another, the revenue data derive from different administrative sources than the payroll tax data. Most of the matches between the payroll tax and revenue data are via Employer Identification Numbers (EINs) but firms can use different EINs for filing income taxes and filing quarterly payroll taxes.[11] For such firms, name and address matching is required. Haltiwanger et al. (2017) also show that the missingness of revenue is only weakly related to observable firm

[10]See for example Decker et al. (2020). In their calibrated model of labor adjustment frictions, they obtain a correlation of TFP and revenue labor productivity of 0.90.

[11]Another source of mismatch is sole proprietors file income taxes on their individual income tax returns while payroll taxes are filed via their EIN. Administrative data are available that links the EINs to the filers via the SS-4 form (application for EINs). While this information is incorporated in the Census Business Register, it is imperfect.

characteristics such as industry, size, or age.[12] We are able to construct measures of labor productivity at the firm (operational control) level given that the Census Business Register has a complete mapping of all EINs owned by any given parent firm. Even with these limitations, we have revenue per worker for more than 4 million firms in each calendar year which we integrate with the LEHD data infrastructure via EINs. For the remaining private-sector employers in the LEHD data for which we cannot match to our productivity data, we impute labor productivity using the size, age, and relative wages paid by the employer within their industry.[13]

2.1 Productivity, Growth, and Survival

Our measure of firm productivity–based on revenue per worker–exhibits a number of the key features that Syverson (2011) emphasized are common in the literature on firm productivity and dynamics. First, we find tremendous dispersion of revenue labor productivity within narrowly defined sectors. The within industry/year standard deviation of log real revenue per worker is about 0.80. This is in the range of labor productivity dispersion indices reported by Syverson (2004). Second, we find that log real revenue per worker is highly predictive of firm growth and survival, as shown in Table 1.[14] We consider two dependent variables for all incumbents in period t-1. The first dependent variable is the Davis, Haltiwanger, and Schuh (1996) firm level growth rate of employment that is inclusive of firm exit from t-1 to t.[15] The second dependent variable is an exit indicator that takes on the value of one if the firm exits between t-1 and t and is zero otherwise. We use a linear probability model for this second specification. Firm exit and growth is organic growth and exit in the manner defined

[12] The productivity data explicitly excludes North American Industry Classification System (NAICS) 81 which is Other Services. This industry is very heterogeneous, including non-profits such as religious organizations where productivity is not well defined.

[13] The latest year for which we have firm productivity data is 2015, so we end our time series there although the LEHD data are more current. We investigated imputing post-2015 productivity using lagged productivity and other covariates but were not satisfied this 100 percent imputation was of sufficiently high quality. In unreported results, we have found that the patterns of worker flows are robust to excluding the imputed cases. Including the imputed cases facilitates our quantification of shares of employment at high and low productivity firms and in turn the productivity decomposition we use in the analysis.

[14] For this analysis, we do not restrict the sample to those firms in our LEHD data sample. These regressions use all firm-year observations from the revenue-enhanced Census Business Register.

[15] This measure is given by $g_{it} = (E_{it} - E_{it-1})/(0.5 * (E_{it} + E_{it-1}))$. It is a second order approximation to a log first difference that accommodates entry and exit.

Table 1: Productivity, Employment Growth, and Firm Death

	Employment Growth Rate (1)	Firm Death (2)
Productivity	0.216	-0.066
	(0.00011)	(0.00005)
Log of firm size	0.056	-0.045
	(0.00006)	(0.00002)

Notes: Each column presents estimates from a separate regression. The dependent variable in column 1 is the employment growth rate between the current and subsequent year and the dependent variable in column 2 is an indicator equal to one of the firm dies in the subsequent year. The independent variables in each regression are the log of firm size and productivity, which is defined as the log revenue per worked deviated from the industry (defined by the 4-digit NAICS code) average. Standard errors are presented in parentheses.

by Haltiwanger, Jarmin, and Miranda (2013) (i.e., it abstracts from changes in ownership or M&A activity). We regress these two outcomes on the deviation of log productivity from the industry average in t-1 and on log size in t-1 (log of firm employment in t-1). While these are simple reduced form specifications, these specifications are consistent with standard models of firm growth and survival since these are proxies for the two key state variables for the firm in making growth and survival decisions. The canonical model implies that holding initial size constant a firm with higher productivity is more likely to grow and less likely to exit. We find overwhelming evidence in support of these predictions in Table 1. A one standard deviation increase in within-industry productivity yields a 20 percentage point increase in net employment growth and 5 percentage point decrease in the likelihood of exit.[16]

These descriptive results give us confidence to proceed with our measure of revenue labor productivity since we produce patterns that others have found using TFP measures in sectors such as manufacturing. In line with the existing literature, our findings of a tight relationship between firm productivity, growth, and survival are consistent with the hypothesis that there are intrinsic differences in productivity across firms that help account for the high rate of reallocation of jobs across firms. In addition, such intrinsic differences in productivity have implications for worker reallocation including the potential role of a productivity job ladder.

[16]Decker et al. (2020) develop a simple model of firm dynamics with adjustment frictions that shows that the relationship between growth and survival from t-1 to t with realizations of labor productivity in period t is very similar as with TFP, holding firm size constant in t-1.

2.2 Defining High- and Low-Productivity Firms

To help mitigate remaining concerns about measurement error, we construct robust rankings of firms by productivity. We first generate time-invariant measures of employer productivity, defined as the employment-weighted average of firm productivity over the life of the SEIN (the state tax identifier number, the key employer identifier in LEHD data). This approach is broadly consistent with the rank preserving equilibria assumption in Moscarini and Postel-Vinay (2013). We then compute the employment-weighted and within-industry quintiles of the productivity distribution. Using these quintiles, we define high-productivity firms as those in the top two quintiles and low-productivity firms as those in the bottom three quintiles. In unreported analysis, we find that results are robust to permitting firms to change ranks over time. This is not surprising given the large differences between high- and low-productivity firms. For example, the within-industry differences in average gross output per worker between high- and low-productivity firms are typically in excess of 85 log points.

As a robustness check on our productivity measure, we also rank firms by the AKM firm fixed effect and average earnings. We estimate the AKM firm premiums by regressing log earnings on person fixed effects, firm fixed effects, and controls for time and worker age.[17] We estimate the model by implementing the iterative method proposed by Guimaraes and Portugal (2010). The AKM firm fixed effect abstracts from observable and unobservable individual characteristics and in canonical models, the firm specific pay premia should be closely related to productivity differences across firms. We also consider simple non-parametric measures of relative earnings by ranking firms based on the average log earnings of full-quarter workers. Just as we do for gross output per worker, we construct employment-weighted within-industry quintiles based on these measures and define high-ranked firms as those in the top two quintiles and low-ranked firms as those in the bottom three quintiles.

[17] To control for time we include a set of year dummies that capture calendar year effects on earnings. To control for worker age, we follow the specification of Card, Cardoso, and Kline (2016). We center age around 40, include a quadratic and cubic transformation of worker age, but omit the linear term. Note that we estimate our AKM employer effects at the State Employer Identification Number level rather than the national level as in our productivity data. This method of estimating AKM effects follows the conventional implementation strategy when applied to LEHD data. This distinction should have a minimal effect on whether an employer is counted as low- vs. high-ranked.

3 Worker Flows Over the Business Cycle

We begin by examining how job-to-job moves and worker flows through nonemployment reallocate workers across high- and low-productivity firms. To understand how worker reallocation moves workers from one group of firms to another, we use the following identity:

$$\text{Net Job Flows} = H_t - S_t = \sum_{i \in \{p,n\}} (H_t^i - S_t^i) = \sum_{i \in \{p,n\}} \sum_{j \in \{l,h\}} (H_t^{ij} - S_t^{ij}) \tag{1}$$

where H_t is the number of hires and S_t is the number of separations in quarter t. The superscripts denote subsamples defined by the type of worker flow, where $i = p$ denotes poaching (job-to-job) flows and $i = n$ denotes flows through nonemployment, and the type of firm, where $j = h$ denotes high-productivity firms and $j = l$ denotes low-productivity firms.[18] For example, H_t^p denotes poaching hires and H_t^{ph} denotes poaching hires at high productivity firms. We convert all flows to rates by dividing through by employment in time $t - 1$.[19] We seasonally adjust all series using the X-12 procedure.

The identity in equation 1 decomposes employment growth at high-productivity firms (H_t^h-S_t^h) into net growth due to two components: job-to-job moves of workers or poaching flows (H_t^{ph}-S_t^{ph}) and flows of workers through nonemployment (H_t^{nh}-S_t^{nh}).[20] In the aggregate economy, employment growth is entirely attributable to net worker flows through nonemployment since poaching hires and poaching separations aggregated over both high- and low-productivity firms are equal. However, for any subset of firms in the economy, net poaching need not be zero, as some firms will be more successful poaching workers away from other employers. This "net poaching flows" component of growth captures the comparative growth advantage one group of firms has over another in their ability to attract workers away from other firms.

Figure 1 shows our decomposition of net job flows for high- and low-productivity firms.

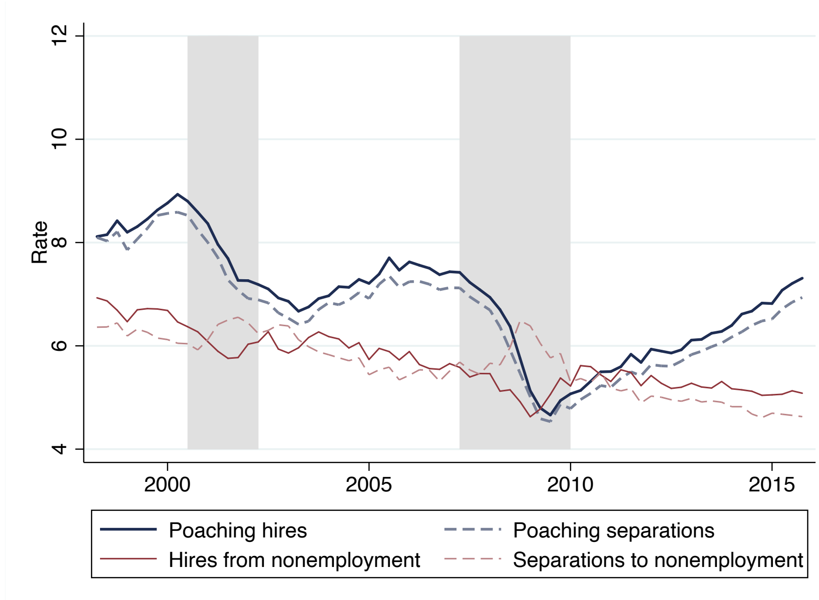
[18] A given type of firm (e.g., high-productivity) may have workers that are hired by that firm via a job-to-job flow and separate from that firm via a job-to-job flow. We refer to the former as a poaching hire and the latter as a poaching separation.

[19] Hires and separations characterize worker mobility between time $t - 1$ and t. For hires we count all worker flows into a firm in our sample at time t. For separations, we count all worker flows out of a firm in our sample at time $t - 1$.

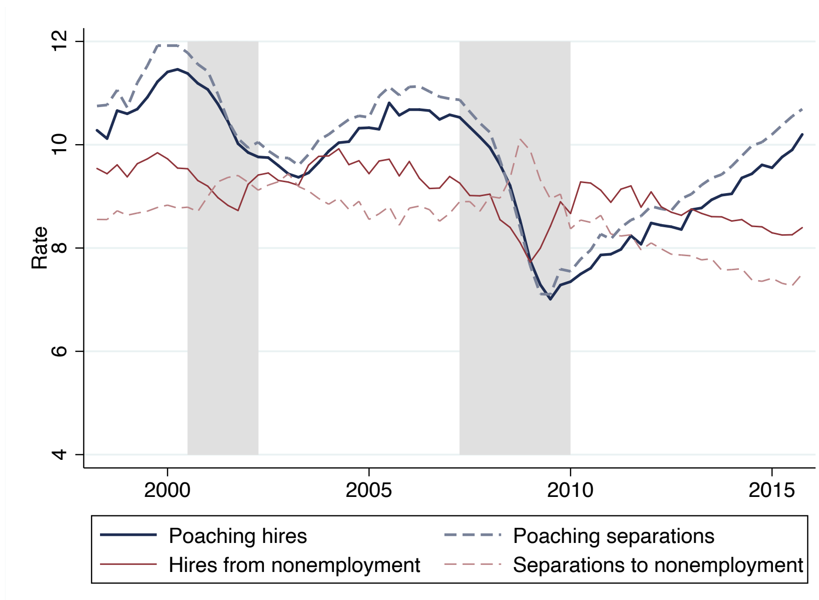
[20] Correspondingly for low-productivity firms, H_t^l-S_t^l = (H_t^{pl}-S_t^{pl}) + (H_t^{nl}-S_t^{nl}).

Figure 1: Poaching and Nonemployment Flows by Firm Productivity

(a) High-Productivity Firms



(b) Low-Productivity Firms



Notes: High-productivity indicates that the firm is in the top two quintiles of the within-industry productivity distribution. Low-productivity indicates the firm is the bottom three quintiles of the within-industry productivity distribution. Data are seasonally adjusted using X-12. The shaded regions mark quarters in which there was a recession.

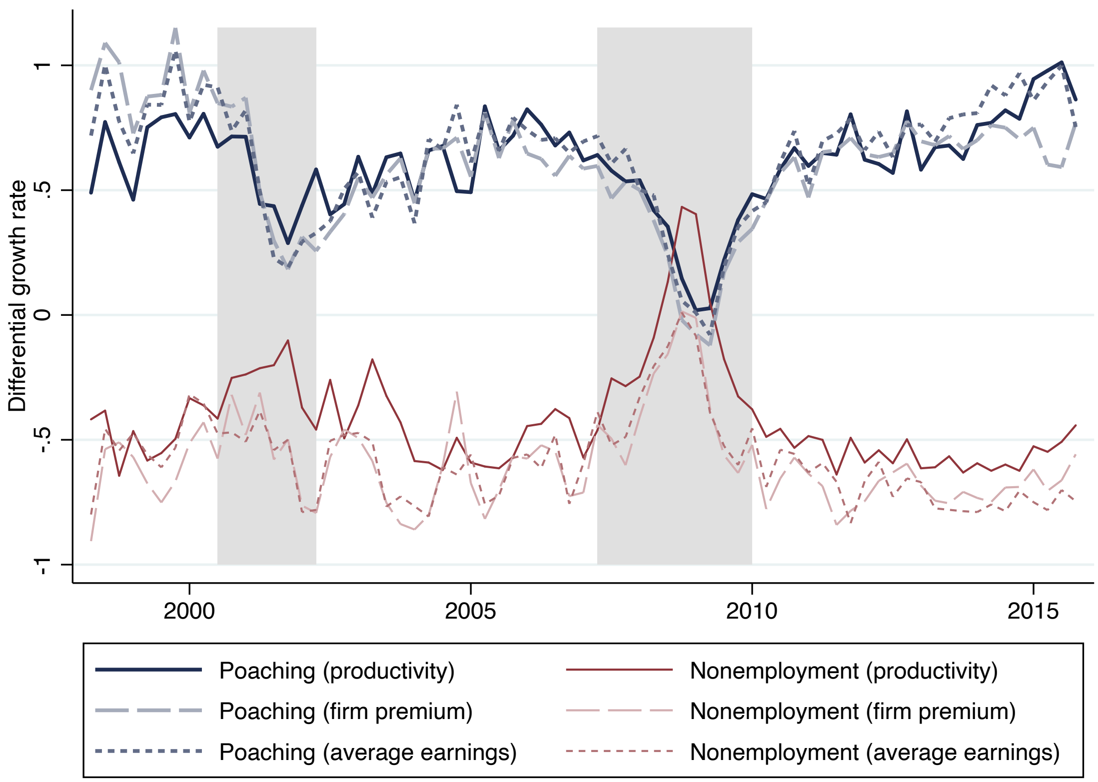
As discussed previously, a key prediction of job ladder models is that job-to-job moves should reallocate workers away from less productive to more productive firms. Figure 1(a) shows that this prediction from the theory holds true in the data. The most productive firms have overall positive net employment growth on average and net poaching (H_t^{ph} - S_t^{ph}) is strongly positive. The average net employment growth of high-productivity firms is 0.33 percent per quarter with net poaching (the rate at which job-to-job moves reallocate workers to high-productivity firms) averaging 0.27 percent per quarter. In other words, during the 1998-2015 period, job-to-job moves of workers from less-productive employers account for most (80 percent) of the net employment growth of high-productivity firms.

The results of the decomposition are also striking for the less productive firms in the industry. In Figure 1(b), low-productivity firms grew at a rate of 0.14 percent per quarter on average from 1998-2015, which is slower than the high-productivity firms. Low-productivity firms lose -0.34 percent employment per quarter from workers "voting with their feet" and moving to firms ranked higher in firm productivity distribution. The positive growth rate for less productive firms is entirely due to strong hiring from nonemployment. In other words, in a typical quarter less productive firms recruit from the pool of unemployed individuals to replace workers moving to better firms. This is also consistent with job ladder models of the labor market. In job ladder models, it is the search and matching frictions that support the presence of low-productivity firms that primarily hire from nonemployment.

The patterns of hires and separations in Figure 1 are instructive for understanding the differences in the cyclical dynamics of job-to-job and nonemployment worker flows. Poaching hires and separations both decline for high-productivity firms in contractions with the decline in poaching hires larger so that net poaching declines significantly. Hires from nonemployment decline sharply for low-productivity firms in contractions accompanied by a surge in separations so that net employment growth declines sharply for low-productivity firms. There are similar qualitative patterns for hires from and separations to nonemployment for high-productivity firms but the magnitudes are smaller.

To more clearly see how worker flows reallocate workers across the productivity ladder, we decompose the average overall net job flow differential between high- and low-productivity groups into the net poaching differential and the net flows from nonemployment differential.

Figure 2: Differential Flows between High- and Low-Ranked Firms



Notes: Differential growth rates are the difference in quarterly employment growth rates between firms in the high category (top two quintiles) and those in the low category (bottom three quintiles). The different series present results in which the high and low categories are defined by productivity, average log earnings, and the AKM firm premium. For all measures, the quintiles are calculated within NAICS 4-digit industry codes. Results are presented separately for poaching and nonemployment flows. Data are seasonally adjusted using X-12. The shaded regions mark quarters in which there was a recession.

Let E_{t-1}^j denote employment at firm type j at time $t-1$. Then $\lambda_t^i = (H_t^{pj} - S_t^{pj})/E_{t-1}^j$ and $\delta_t^j = (H_t^{nj} - S_t^{nj})/E_{t-1}^j$ are the employment growth rates at firm type $i \in \{l, h\}$ through net poaching flows and net nonemployment flows, respectively. Figure 2 plots the differential rates between high- and low-productivity firms–i.e., $\lambda_t^h - \lambda_t^l$ and $\delta_t^h - \delta_t^l$. The average net poaching differential between high- and low-productivity firms is 0.61 percent per quarter. It is also quite cyclical: a minimum of 0.012 in 2009Q1, and a maximum of 1.01 in 2015Q3. The average net nonemployment differential is -0.41 percent, but this increases at the onset of economic downturns.[21] The negative contribution of flows through nonemployment to the differential growth rates of high- and low-productivity firms implies that search frictions are a drag on productivity-enhancing reallocation in expansions, allowing mediocre firms to attract workers flowing through nonemployment who cannot immediately find better jobs.

For comparison purposes, we also show in Figure 2 the differential growth rates for firms ranked by AKM firm fixed effects and average earnings. To make results comparable, the rankings are calculated within industries. These patterns are very similar to those from the job ladder decomposition of growth rates when firms are ranked by productivity, both in levels and business cycle dynamics. The striking similarity between these three measures is again consistent with job ladder models of the labor market, where high-productivity firms offer higher wages, and grow faster than less-productive firms in expansions by poaching workers away from less-productive, lower-paying firms. The strong similarity between the productivity and AKM fixed effects results also provides reassurance about measurement error concerns about the revenue productivity measure.

Figure 2 also shows pronounced cyclical patterns that differ across the components of net job flows. We quantify the nature of that variation in Table 2. Table 2 presents the results from regressions where each component of the differential growth rate (net job flows, net poaching flows, and net nonemployment flows) is regressed on a cyclical indicator and a time-trend. Each column represents the results of these regressions for firms when they are ranked by productivity, AKM firm fixed effects, and average firm earnings

[21] Not shown in Figure 2 is the overall net job flow differential between high and low productivity firms, which is the sum of the poaching and nonemployment margins, and averages 0.20 percent per quarter. It reaches a maximum of 0.58 in 2008Q4 and a minimum of -0.13 in 2004, an expansion year. In the set of regressions in Table 2 we will test the cyclicality of this overall redistribution.

Table 2: Differential Net Job Flows Over the Cycle

	High-Low Differential		
	(1)	(2)	(3)
A. Net Job Flows			
Change in unemployment rate	0.136	-0.179	-0.170
	(0.060)	(0.084)	(0.084)
Deviated unemployment rate	-0.086	-0.161	-0.144
	(0.023)	(0.029)	(0.030)
B. Poaching Job Flows			
Change in unemployment rate	-0.440	-0.544	-0.560
	(0.049)	(0.063)	(0.061)
Deviated unemployment rate	-0.097	-0.128	-0.103
	(0.027)	(0.033)	(0.034)
C. Nonemployment Job Flows			
Change in unemployment rate	0.576	0.365	0.390
	(0.043)	(0.047)	(0.049)
Deviated unemployment rate	0.011	-0.033	-0.041
	(0.033)	(0.026)	(0.027)
Definition of Job Ladder			
Firms ranked by	productivity	average earnings	firm premium
Firms ranked within	industry	industry	industry

Notes: Each cell presents results from a separate regression estimated on national quarterly data. The dependent variable is the differential worker flow rate between firms on the high and long rung of the job ladder, where the type of flow is indicated by the panel label. The job ladder is defined by productivity, average log earnings, and the AKM firm premium in columns 1, 2, and 3, respectively. The independent variables in each regression include a cyclical indicator as well as a linear time-trend and a constant, which are not reported. The cyclical indicators considered include the change in the unemployment rate and the deviations of unemployment from the Hodrick-Prescott trend. Aside from the linear trend, all dependent and independent variables are measured in percentage point units. Standard errors are presented in parentheses.

per worker. Because the results for all three columns are very similar (as suggested by Figure 2) we focus our discussion on the business cycle dynamics of worker reallocation across high- and low-productivity firms (column 1). Two cyclical indicators are used: the change in unemployment and unemployment deviated from a Hodrick-Prescott (HP) trend. Periods of rising unemployment correspond closely to NBER defined recessions. In contrast, unemployment remains substantially above trend well into NBER defined recoveries.

We start by focusing on the net poaching differentials (row B) which shows that net poaching from low- to high-productivity firms decreases in cyclical downturns. This occurs in recessions: for every one percentage point increase in the change in the unemployment rate, the high vs. low net poaching differential declines by 0.440 percentage points. Poaching flows are also low in the times of high unemployment that follow recessions. For every percentage point that the unemployment rate is above its HP trend, the net poaching differential is lower by 0.097 percentage points. These findings are consistent with a sullying effect of recessions.

There is also evidence of a cleansing effect that works through flows to and from nonemployment (row C). The net flows from nonemployment differentials provide an indication of the reallocation of employment from low- to high-productivity firms that involves transitions to and from nonemployment. These transitions inherently involve intervening spells of nonemployment. In that respect, this type of reallocation is more costly than job-to-job flows since it involves the time and resource costs of nonemployment. Row C indicates that the reallocation that works through the nonemployment margin is countercyclical. When the change in the unemployment rate increases by one percentage point, differential net nonemployment hiring for high vs. low increases by 0.576 percentage points. This is a cleansing effect of recessions that is working in the opposite direction of job-to-job flows and primarily occurs because there is a disproportionately large spike in separations into nonemployment from low-productivity firms.[22] This cleansing effect,

[22] The differential net flows from nonemployment ($\delta_t^h - \delta_t^l$) can be decomposed into the hires component ($H_t^{nh}/E_{t-1}^h - H_t^{nl}/E_{t-1}^l$) minus the separations component ($S_t^{nh}/E_{t-1}^h - S_t^{nl}/E_{t-1}^l$). Regressing these components against the change in the unemployment rate and controlling for the time-trend produces a point estimate of 0.165 for hires and -0.411 for separations (the difference between these coefficients is 0.576, which is the coefficient found in Table 2). Thus, when the unemployment rate rises, worker reallocation from low- to high-productivity firms through nonemployment increases primarily because of a disproportionate spike in separations to nonemployment from low-productivity firms but also because a disproportionate decline in the rate at which low-productivity firms hire jobless workers.

however, is almost negligible in the times of high unemployment that follow recessions. An additional percentage point of the unemployment rate above its HP trend is associated with only an increase of 0.011 in the net nonemployment differential.

The coefficient on overall net job flow differentials (row A) is determined by the cleansing and sullying effects. During recessions, cleansing effects are stronger than sullying effects. A one percentage point increase in the change in the unemployment rate is associated with an increase in the relative employment growth of high-productivity firms of 0.136 percentage points. In the times of high unemployment that follow recessions, cleansing effects are small and so sullying effects dominate. An additional percentage point of the unemployment rate above its HP trend is associated with an increase in the relative employment growth of low-productivity firms of 0.086 percentage points. Thus, Table 2 illustrates that the relative importance of cleansing and sullying effects varies at different phases of the business cycle.

4 Implications for Aggregate Outcomes

What are the implications of the business cycle dynamics described in the previous section on aggregate productivity growth? The decline in productivity-enhancing reallocation through job-to-job moves in slack labor markets should be a drag in productivity growth, while higher rates of job destruction at less-productive firms in downturns ought to free resources for more productive use. The magnitude of the effect on aggregate productivity growth will depend on both the size of the differential employment flows as well as the productivity differential between high- and low-productivity firms. In this section we formalize this intuition and implement a decomposition exercise to quantify how worker reallocation through poaching and nonemployment flows contributes to aggregate productivity growth, and how these components of productivity growth vary over the business cycle.

4.1 Worker Reallocation and Employment Shares

We begin by focusing on how worker reallocation affects the share of workers at high- and low-productivity firms. We focus initially on the findings using our gross output per worker measure of productivity.[23] We use the following identity to write changes in the share of employment at high-productivity firms as a function of the differential net poaching rates $(\lambda_t^h - \lambda_t^l)$ and differential net nonemployment rates $(\delta_t^h - \delta_t^l)$,

$$\Delta\theta_t^h = \tilde{\lambda}_t^h + \tilde{\delta}_t^h + \tilde{\epsilon}_t^h \tag{2}$$

where $\tilde{x}^h = (x^h - x^l)\theta_{t-1}^h \theta_{t-1}^l (E_{t-1}/E_t)$ for $x \in \lambda, \delta$ and $\Delta\theta_t^h$ is the change in the share of employment at high-productivity firms between quarter t and $t-1$. This expression shows that the sign of differential net poaching rate, $\lambda_t^h - \lambda_t^l$, determines whether poaching rates will increase or decrease the share of employment at high-productivity firms. The magnitude of this effect also depends on the share of workers at high productivity firms as well as the growth in overall employment. See Appendix B for details.

There are two reasons for the existence of the residual term, $\tilde{\epsilon}^h$.[24] First, some workers may move to or from an employer located in a state outside of our 28-state sample. In contrast to the results from the previous section and because we aim to implement an exact decomposition, the counts of hires and separations in this section only include worker flows where both the origin and destination employers are in one of the 28 states in our sample. Second, the administrative code that identifies the employer, the SEIN, can change over time and create a spurious flow of workers between the old and new SEIN. We are able to flag when these changes occur and omit these flows from the poaching and nonemployment flows. However, there is no straightforward way to account for this issue when measuring productivity. Thus, a change in an SEIN could lead to a change in the share of workers at high productivity firms but have no corresponding flow of workers. In unreported results, we directly measure flows of workers in and out of the states in our sample and show that the residual term is primarily attributable to changes in the SEIN over time, not migration in and out of the sample.

Regardless of the source, these residuals flows are both small in magnitude and do

[23] As discussed, this is a relative measure for firms within industries. Using a relative measure within industries somewhat complicates the interpretation of the accounting decomposition we develop and analyze below. Later in the analysis we consider the AKM firm premia measure which overcomes these limitations.

[24] Empirically, we measure the residual term as the difference between the observed changes in employment at high- and low-productivity firms and the changes predicted by the poaching and nonemployment flows.

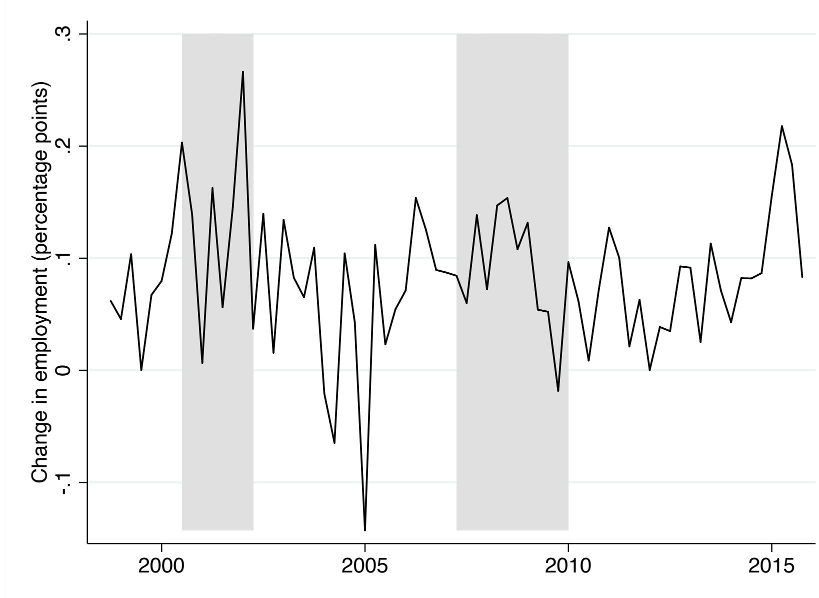
not exhibit a clear pattern across the business cycle. Specifically, the average size of the differential net poaching and nonemployment growth rates are three and five times as large as the differential residual flows, respectively. Figure A.1 in Appendix A presents a version of Figure 2 that contains the residual flows as well as the poaching and nonemployment flows constructed with and without the restriction that both origin and destination employers are in the 28-state sample. The results indicate that the residual flows do not exhibit any notable cyclicality across the business cycle and the differential net poaching and nonemployment growth rates that exclude workers moving in and out of our 28-state sample are very similar (in levels and movements across time) to the results from Figure 2. We infer that this residual term is not important for the main results discussed in this section.

Figure 3 shows the time series of the main components of the decomposition in equation 2 and illustrates how worker reallocation affects the percent of employment at high-productivity firms.[25] Figure 3(a) presents the observed changes in the percent of employment at high-productivity firms between the current and previous quarters ($\Delta\theta_t^h$). Figure 3(b) presents the components of these changes that are attributable to worker reallocation through poaching flows ($\tilde{\lambda}^h$) and nonemployment flows ($\tilde{\delta}^h$). During expansions, worker flows through nonemployment lead to a reduction in the share of workers at high-productivity firms whereas poaching flows lead to an increase in the share of workers at high-productivity firms. At the onset of a recession, the rate at which nonemployment flows contributes to the growth of employment share of low-productivity firms slows. Indeed, in the Great Recession this change was large enough such that nonemployment flows briefly contributed positively to the growth of the employment share at high-productivity firms. Throughout our sample period, poaching flows always contribute positively to the growth of employment at high productivity firms, but this largely collapses during recessions, particularly in the Great Recession. Consistent with our earlier analysis, the results highlight the staggered nature of the timing of these two effects. The cleansing effect begins at the onset of a recession where as the sullying effect starts and peaks later on.

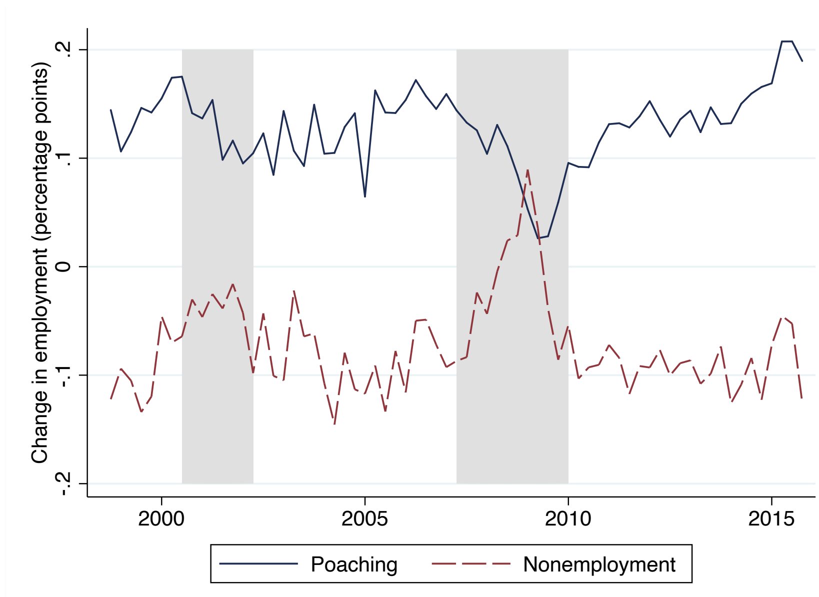
[25] To make the figure more readable, we present the results in percentage point terms.

Figure 3: Changes in Percent of Employment at High-Productivity Firms

(a) Observed Changes



(b) Contribution of Worker Reallocation



Notes: Panel (a) presents the first difference of the percent of employment at high-productivity firms. Panel (b) presents the change in the percent of employment at high-productivity firms that is attributable to worker reallocation through poaching and nonemployment flows. Data are seasonally adjusted using X-12. The shaded regions mark quarters in which there was a recession.

4.2 Worker Reallocation and Productivity

We now quantify how changes in the share of workers at high-productivity firms affects an index of aggregate productivity growth using the productivity differential between the two groups of firms. Our analysis focuses on a measure of productivity that is the employment-weighted average of a firm-level measure of productivity, which is measured in logs. Such accounting indices of productivity have been widely used in the literature to quantify the contribution of reallocation effects to productivity (e.g., Olley and Pakes, 1996; Foster, Haltiwanger, and Krizan, 2001; and Melitz and Polanec, 2015). As we discuss in Appendix A, an aggregate index based on employment-weighted firm-level labor productivity indices track official statistics from the U.S. Bureau of Labor Statistics (BLS) quite well.[26]

Let, R_t denote the employment-weighted average of the firm-level measure of log revenue per worker in quarter t. Then, $R_t = \theta_t^l R_t^l + \theta_t^h R_t^h$, where R_t^i denotes the employment-weighted average of the firm-level measure of log revenue per worker within firm type i in quarter t and θ_t^i is the share of employment at firm type i in quarter t.[27] An increase in θ_t^h leads to an increase in R_t but the interpretation of a change in R_t is complicated by the fact that log revenue per worker is a measure of productivity that is not readily comparable across industries. Let P_t denote an unobserved measure of productivity that is the weighted average of a firm-level measure of productivity, which is comparable across industries.

Our goal is to use the observed measure of log revenue per worker in order to quantify how changes in θ_t^h affect P_t. We achieve this goal by making the following two assumptions:

[26] See also Figure A.1 in Decker et al. (2017). Conceptually, this aggregate index is consistent with aggregate productivity in a structural model with a single input (labor), constant returns to scale, and perfect competition in product markets. While these are strong assumptions (although not inconsistent with job ladder models), as noted such indices track official statistics closely. Much of the literature that focuses on misallocation specifies curvature in the revenue function so that there is a well-defined size distribution even in the absence of distortions. Part of the reason for this is that this enables a measure of allocative efficiency that is relative to a frictionless/distortionless benchmark (e.g., Hsieh and Klenow, 2009; Bartelsman et al., 2013; and Blackwood et al., forthcoming). In principle, such curvature is not necessary in models with adjustment frictions such as search and matching frictions. Models with curvature in the revenue function have the property that it is not optimal to allocate all resources to the most productive firm. While this implies caution in using weighted average measures of firm-level productivity in quantitative analysis of models with such curvature, Decker et al. (2020) show that in models with adjustment frictions that this type of aggregate productivity index tracks structural measures of true productivity well even if there is curvature in the revenue function.

[27] While the firm type (high- or low-productivity) is time invariant, the firm-level measures of productivity used to construct R_t^i are measured in time t.

A1. $P_t^i(k) = R_t^i(k) + U_t(k)$, where $R_t^i(k)$ denotes the employment-weighted average of the firm-level measure of log revenue per worker within industry k, firm type i, and quarter t; $U_t(k)$ is an unobserved term that is constant within industry and quarter; and $P_t^i(k)$ is the employment weighted average of the unobserved measure of productivity within industry k, firm type i, and quarter t.[28]

A2. $\Delta\big(cov\big(\theta_t^i(k), \tilde{R}_t^i(k)\big)\big) = 0$, where $\theta_t^i(k)$ is the share of employment at firm type i within industry k and quarter t, $\tilde{R}_t^i(k) \equiv R_t^i(k) - (R_t^l(k) + R_t^h(k))/2$, and Δ denotes the difference between quarter t and $t-1$.

Assumption A1 states that, up to an additive term that is constant within industry and quarter, log revenue per worker is a measure of productivity that is comparable across industries. Assumption A2 states that the covariance between the share of employment at high-productivity firms and the dispersion of log revenue per worker does not change over time. Appendix B presents empirical evidence that supports the plausibility of assumptions A1 and A2.

Assumptions A1 and A2 allow us to isolate productivity growth that arises from worker reallocation between high- and low-productivity firms. By an accounting identity we can rewrite the unobserved measure of aggregate productivity as an employment-weighted average of firm type by industry averages, $P_t = \sum_k \theta_t(k)[\theta_t^l(k)P_t^l(k) + \theta_t^h(k)P_t^h(k)]$. Combining this accounting identity with assumptions A1 and A2 implies the following expression for this index of aggregate productivity growth,

$$\Delta P_t = \underbrace{(\tilde{R}_{t-1}^h - \tilde{R}_{t-1}^l)\Delta\theta_t^h}_{\text{Worker Reallocation}} + \theta_t^l \Delta \tilde{R}_t^l + \theta_t^h \Delta \tilde{R}_t^h + \Delta\left(\sum_k [\theta_t(k)\bar{P}_t(k)]\right) \tag{3}$$

where $\bar{P}_t(k) \equiv [P_t^l(k) + P_t^h(k)]/2$. The first term, $(\tilde{R}_{t-1}^h - \tilde{R}_{t-1}^l)\Delta\theta_t^h$, is the component of productivity growth attributable to worker reallocation between high- and low-productivity firms.[29] The remaining terms capture other aspects of productivity growth, which include productivity growth driven by firm-level innovations unrelated to worker reallocation. See

[28] Recall that $P_t^i(k)$ is a measure of productivity that is directly comparable across industries.

[29] While our classification of high- and low-productivity firms is based on a within-industry ranking of log revenue per worker, our worker flows data are not restricted to within-industry job flows.

Appendix B for a details.

We can further decompose the component of productivity growth attributable to worker reallocation between high- and low-productivity firms into the components attributable to poaching, nonemployment, and residuals flows. Specifically, combining equation 2 with the first term in equation 3, yields,

$$\underbrace{(\tilde{R}^h_{t-1} - \tilde{R}^l_{t-1})\Delta\theta^h_t}_{\text{Worker Reallocation}} = \underbrace{(\tilde{R}^h_{t-1} - \tilde{R}^l_{t-1})\tilde{\lambda}^h_t}_{\text{Poaching}} + \underbrace{(\tilde{R}^h_{t-1} - \tilde{R}^l_{t-1})\tilde{\delta}^h_t}_{\text{Nonemployment}} + \underbrace{(\tilde{R}^h_{t-1} - \tilde{R}^l_{t-1})\tilde{\epsilon}^h_t}_{\text{Residual}} \tag{4}$$

An increase in the share of workers at high-productivity firms increases the index of aggregate productivity, and the magnitude of the effect is determined by the productivity differential between high- and low-productivity firms. The analysis in this section uses equation 4 to decompose productivity growth attributable to worker reallocation (between high- and low-productivity firms) through poaching and nonemployment flows.

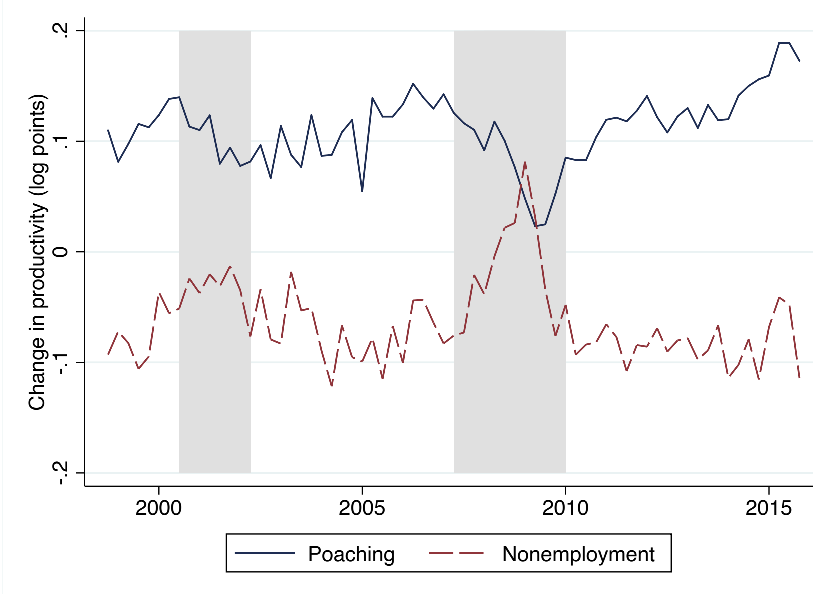
Figure 4(a) presents the decomposition of productivity growth into components attributable to poaching and nonemployment flows and shows clear evidence of the cleansing and sullying effects of recessions. On average, worker reallocation through poaching flows contributes 0.1 log points to overall productivity growth each quarter (all statistics on productivity changes are quarterly and have not been annualized). This is a substantial contribution to the overall quarterly average rate of productivity growth of 0.33 when aggregating our micro data.[30] However, during recessions there is clear evidence of a sullying effect. In 2006:1 the poaching contribution is 0.13 log points but this declines to 0.02 by 2009:2. In contrast, worker reallocation through nonemployment tends to be a drag on productivity growth, on average, decreasing productivity by 0.67 log points each quarter.[31] However, during recessions there is evidence of a cleansing effect since during those times nonemployment flows yield declines in the employment share of low-productivity firms. In 2006:1, the nonemployment component is -0.1 log points but increases to 0.08 in 2009:1. The figure illustrates the staggered nature of these effects in which the cleansing

[30] As discussed in Appendix A, the comparable average quarterly rate using published BLS statistics is 0.43. The aggregate index from our data and from published BLS statistics are highly correlated (0.85).

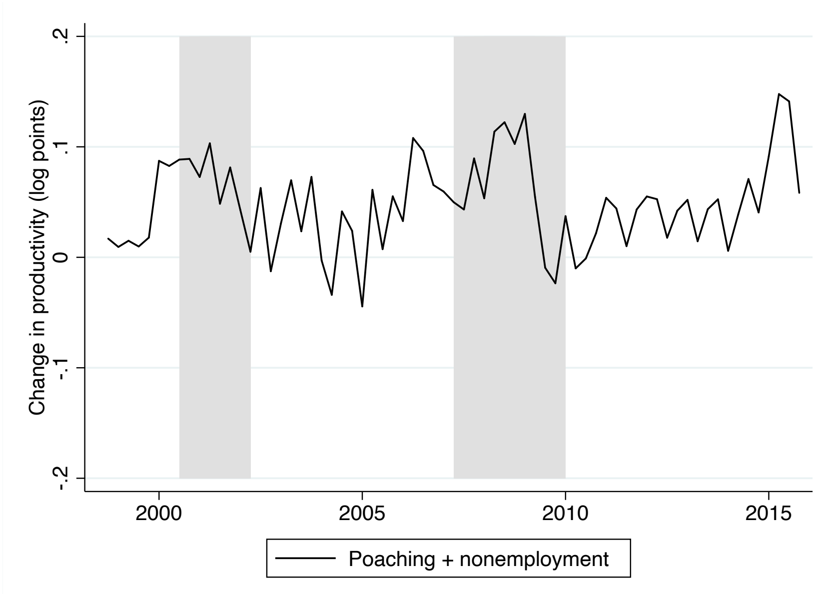
[31] This drag on productivity is consistent with job ladder models with search and matching frictions. Dispersion in productivity is supported by such frictions in equilibrium.

Figure 4: Decomposition of Growth in Productivity Over the Cycle

(a) Poaching and Nonemployment Flows



(b) Combined Effect



Notes: Panel (a) presents the components of quarterly productivity growth that are attributable to worker reallocation between high- and low-productivity firms through poaching and nonemployment flows and Panel (b) presents the sum of these two components. Data are seasonally adjusted using X-12. The shaded regions mark quarters in which there was a recession.

occurs at the outset of the recession–when unemployment rate is rising most rapidly–and the sullying effect peaks relatively further on into the downturn–which the unemployment rate is highest. In addition, the sullying effect lingers well into the recovery.

Figure 4(b) presents the combined effect of worker reallocation through poaching and nonemployment flows. During expansions, the total effect of worker reallocation through poaching and nonemployment flows contributes 0.04 log points to overall productivity growth each quarter. In recessions, this increases to 0.08. While this might suggest that cleansing effects dominate, these calculations neglect the fact that the sullying effect lingers well into the recovery. Using an alternative indicator of the cycle, we find that the combined effect is 0.07 on average for quarters where the unemployment rate is below HP trend and 0.03 on average for quarters where unemployment is above the HP trend. This reversal is driven by much larger contributions of poaching flows during periods of low unemployment (0.13) compared to high unemployment (0.09).

Column 1 of Table 3 summarizes these patterns.[32] Here we show results from a set of regressions where different components of productivity growth are regressed on a cyclical indicator and a time-trend. We use two alternative cyclical indicators: changes in the unemployment rate and deviations of the unemployment rate from the HP trend. Panel B shows that productivity-enhancing reallocation through job-to-job moves is procyclical using both measures. Panel C shows that productivity-enhancing reallocation through worker flows through nonemployment is counter-cyclical using both measures. The net effect in Panel A, however, does depends on the cyclical indicator. Sullying effects dominate when cyclicality is measured using deviations from the unemployment rate: this is because it takes a while for productivity-enhancing reallocation from job-to-job moves to recover in expansions. In contrast, cleansing effects dominate when cyclicality is measured using changes in the unemployment rate. Taken together, these results imply that the cleansing effect peaks earlier in a downturn compared to the collapse of the job ladder that lingers into the early stages of a recovery. These results also suggest that slow labor market recoveries will be generally more damaging to productivity growth than V-shaped recoveries as slow recoveries exhibit an accompanying slow recovery of job-to-job flows.

[32]We discuss columns 2 and 3 of this table in the next section.

Table 3: Productivity Growth from Job Flows Over the Cycle

	Productivity Growth		
	(1)	(2)	(3)
A. Net Job Flows			
Change in unemployment rate	0.040	0.010	0.005
	(0.015)	(0.016)	(0.043)
Deviated unemployment rate	-0.024	-0.026	-0.084
	(0.005)	(0.006)	(0.014)
B. Poaching Job Flows			
Change in unemployment rate	-0.052	-0.062	-0.225
	(0.010)	(0.009)	(0.029)
Deviated unemployment rate	-0.024	-0.021	-0.073
	(0.004)	(0.004)	(0.013)
C. Nonemployment Job Flows			
Change in unemployment rate	0.092	0.072	0.230
	(0.009)	(0.010)	(0.026)
Deviated unemployment rate	0.000	-0.005	-0.012
	(0.006)	(0.005)	(0.015)
Definition of Job Ladder			
Firms ranked by	productivity	firm premium	firm premium
Firms ranked within	industry	industry	full sample

Notes: Each cell presents results from a separate regression estimated on national quarterly data. The dependent variable is the growth in productivity or AKM firm fixed premium as noted by the second to last row. The independent variables in each regression include a cyclical indicator as well as a linear time-trend and a constant, which are not reported. The cyclical indicators considered include the change in the unemployment rate and the deviations of unemployment from the Hodrick-Prescott trend. Aside from the linear trend, all dependent and independent variables are measured in percentage point units. Standard errors are presented in parentheses.

4.3 Robustness to Using the AKM Firm Premium

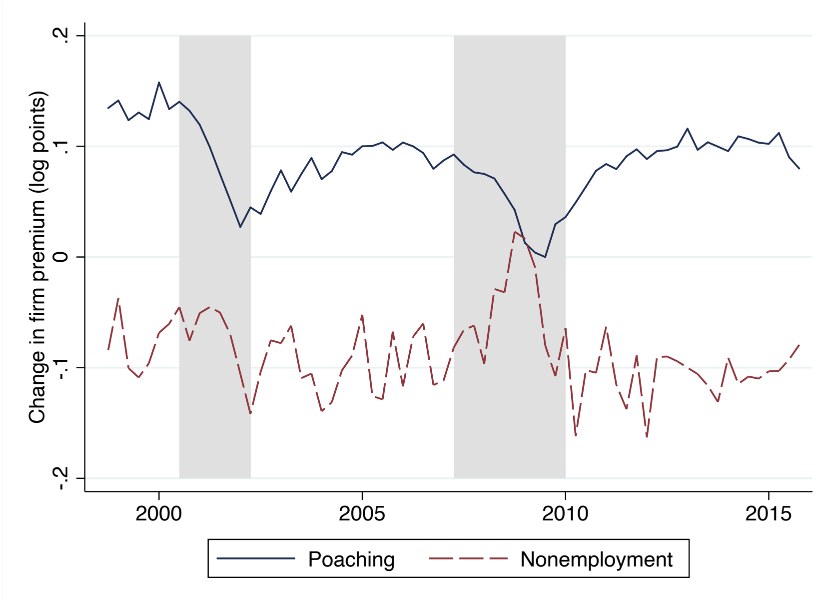
We assess the robustness of our results to using an alternative measure of firm performance: the AKM firm premium. While the revenue per worker measure of productivity has many strengths, it is not easily comparable across sectors and may partially reflect the sorting of workers across firms in addition to innate differences in firm productivity. The AKM firm premium is not subject to these same limitations. Furthermore, canonical models suggest that more productive firms offer higher wages and therefore the AKM firm premium ought to be closely related to innate differences in firm productivity both within and across industries.

Figure 5 decomposes growth in the aggregate firm premium attributable to worker reallocation across the firm premium ladder through poaching and nonemployment flows. Firms are re-ranked into high- and low-premium firms and the worker flows (i.e., $\tilde{\lambda}_t^h$ and $\tilde{\delta}_t^h$) and the differentials in the firm premium (i.e., $\tilde{R}_{t-1}^h - \tilde{R}_{t-1}^l$) are re-calculated to reflect the new rankings and alternative measure of firm performance. Figure 5(a) follows the methodology described in equation 4 but uses the AKM firm premium as the measure of firm performance instead of revenue per worker. Importantly, firms are ranked within 4-digit NAICS industry codes. Unlike the gross output per worker measure, the AKM firm premium is directly comparable across industries. Thus, Figure 5(b) also uses the methodology described in equation 4 but, in addition to using the AKM firm effect as the measure of firm performance, treats all firms as being part of the same industry. In effect, Figure 5(b) ranks firms in the pooled sample and accounts for worker reallocation both within and across industries.

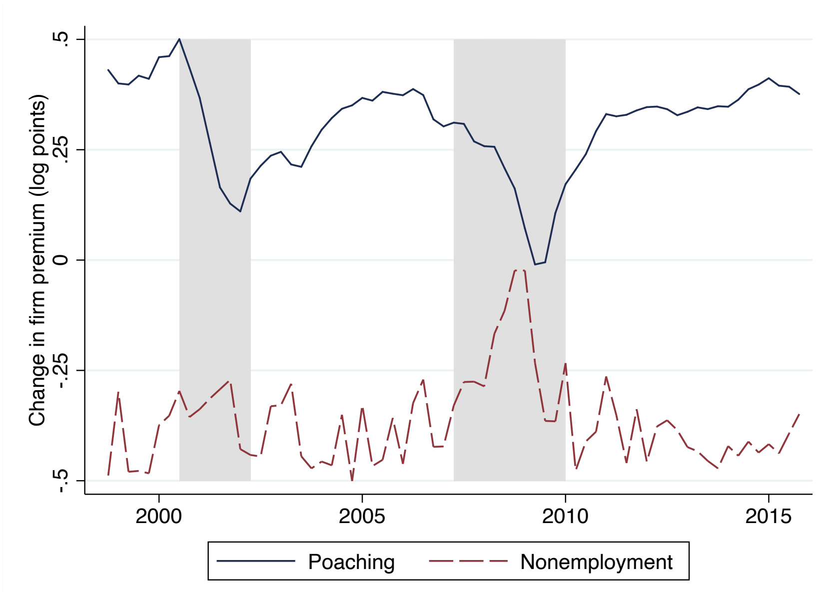
Regardless of the methodology used, both series in Figure 5 present clear evidence of the cleansing and sullying effects that were apparent in worker reallocation across the firm productivity ladder using revenue per worker. For the within-industry rankings, we find that, on average, poaching flows to higher-paying firms lead to an increase in firm premium by 0.09 log points per quarter whereas nonemployment flows lead to a 0.09 log point decrease in the firm premium per quarter. These estimates are quite similar qualitatively and quantitatively to those found in Figuure 4(a), which uses revenue per worker to measure productivity differences within industries. We also find the cyclical patterns of these components are very similar to those using the direct measure of productivity. Figure 5(b) presents estimates

Figure 5: Decomposition of Growth in the AKM Firm Premium Over the Cycle

(a) Firms are Ranked within Industry



(b) Firms are Ranked within the Full Sample



Notes: This figure presents the components of the growth in the average AKM firm premium that are attributable to worker reallocation between high- and low-premium firms through poaching and nonemployment flows. Firms are ranked based on their AKM firm premiums. In panel (a) firms are ranked within their 4-digit NAICS industry codes. In panel (b) firms are ranked within the full sample. Data are seasonally adjusted using X-12. The shaded regions mark quarters in which there was a recession.

based on ranking firms in the pooled sample (not within industry) and finds that, on average, poaching flows contribute 0.3 log points to the growth in the AKM firm premium each quarter whereas nonemployment flows lead a decline by 0.4 log points per quarter. The estimates are about three times as large as those for the within industry based tabulations. While much larger in magnitude, the qualitative patterns are very similar.

Columns 2 and 3 of Table 3 quantify the cyclicality of the contributions to the AKM firm premium. As in the column 1, the cleansing contribution outweighs the sullying contribution in response to an increase in the unemployment rate while the opposite is true in response to a positive deviation of the unemployment rate from trend. These findings hold regardless of whether we rank firms within industries (column 2) or in the pooled sample (column 3). Since the AKM firm premium abstracts from worker heterogeneity, this suggests our main results by firm productivity are not being driven by variation in the patterns of sorting of heterogeneous workers across heterogeneous firms over the cycle. The larger coefficients in column 3 relative to column 2 suggest that cleansing and sullying effects are larger in magnitude when inter-industry differentials are accounted for but that the relative contribution of these effects on productivity growth are qualitatively similar.

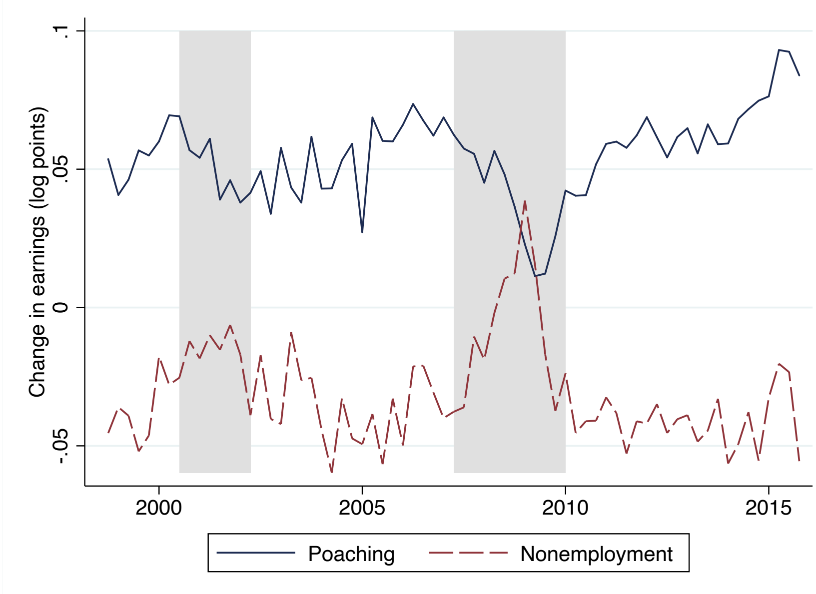
5 Implications for Earnings

Whereas Section 4 focused on implications for productivity growth, the current section asks if moving up the firm productivity ladder benefits workers in the form of higher earnings. We use the same methodology described in equation 4, but we replace the productivity differentials, $\tilde{R}^h_{t-1} - \tilde{R}^l_{t-1}$, with earnings differentials. We measure firm-level earnings in two ways: (i) average log earnings of all workers, and (ii) the AKM firm fixed effect. The earnings differential is the difference between the employment-weighted average of earnings at high- and low-productivity firms. Consistent with our core analysis, we deviate earnings from the industry average when calculating the differentials. Note that the exercise is distinct from the analysis discussed in Section 4.3, since we are investigating the earnings implications of worker flows across firms ranked by the revenue per worker measure of productivity.

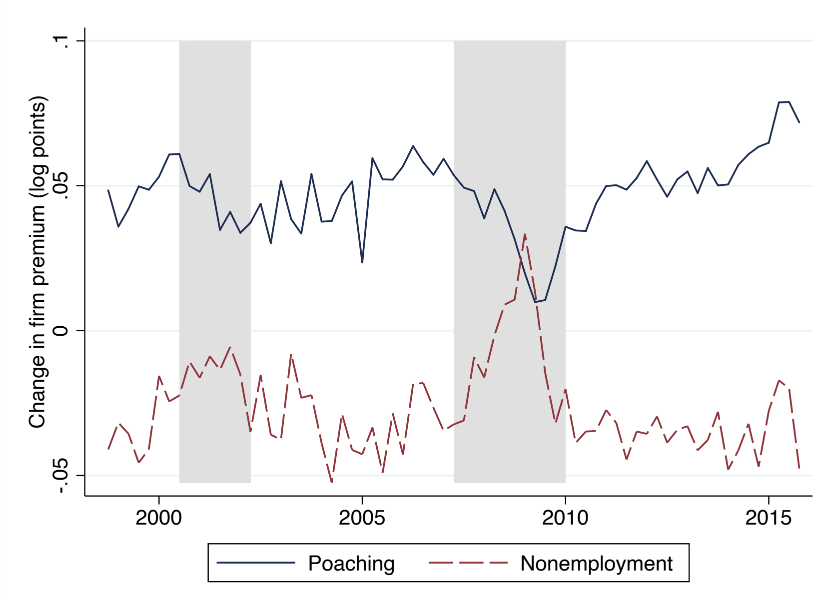
Figure 6 shows that worker reallocation up the firm productivity ladder through poaching

Figure 6: Earnings Growth from Worker Reallocation up the Firm Productivity Ladder

(a) Average Log Earnings



(b) AKM Firm Premium



Notes: The figure shows the components of earnings growth that attributable to worker reallocation between high- and low-productivity firms through poaching and nonemployment flows. Panel (a) uses the differences between the average log earnings of workers at high- and low-productivity firms in order to quantify the implications of changes in the share of workers at high-productivity firms whereas panel (b) uses the AKM firm premium. Data are seasonally adjusted using X-12. The shaded regions mark quarters in which there was a recession.

and nonemployment flows has meaningful implications for the earnings of workers. Figures 6(a) and 6(b) present results in which the earnings differentials are measured with average log earnings and the AKM firm premium, respectively. The results in the two figures are quantitatively and qualitatively similar. Job-to-job transitions add an average of 0.05 log points to average earnings in any given quarter. The earnings contribution of job-to-job flows is lower during recessions. During the 2007-2009 recession, the earnings contribution of job-to-job flows fell to a series low of 0.01. The contribution of nonemployment transitions to earnings growth is in the opposite direction and similar in magnitude to the contribution of job-to-job flows.[33] In the average quarter, worker movements into and from nonemployment subtract an average of 0.03 log points from earnings. This negative effect of nonemployment transitions is less present during recessions. During the 2001 recession, the contribution of nonemployment transitions is close to zero. During the 2007-2009 recession, the contribution of nonemployment transitions to earnings growth is briefly positive.

Comparing these results to Figure 4, we can draw conclusions about the extent to which the gains from productivity-enhancing reallocation are realized by workers. The earnings and productivity implications of employment transitions have similar signs, with job-to-job transitions providing gains, while nonemployment transitions subtract from each. The magnitudes, however, differ. The proportionate changes in earnings are roughly half the magnitude of the analogous changes in productivity. This is suggestive of incomplete pass-through of the gains in revenue productivity from worker flows into earnings.[34]

6 Conclusion

Consistent with the existing literature on firm heterogeneity, we find evidence of large differences in productivity across firms within the same industry. We also find that more

[33]Hahn, Hyatt, and Janicki (2021) consider the implications of employment transitions for earnings growth without considering productivity. They report that job-to-job and nonemployment transitions move in opposite directions and are roughly similar in magnitude, and follow opposite cyclical patterns.

[34]If revenue per worker and the AKM firm premium produced the exact same ranking then we would expect Figure 5(a) and Figure 6(b) to be identical, which they are not. The difference between the two results is partly attributable to the fact that the difference in the average AKM firm premium between high- and low-premium firms (as used in Figure 5(a)) is greater than the difference in the average AKM firm premium between high- and low-productivity firms (Figure 6(b)).

productive firms in the same industry are more likely to grow and less productive firms more likely to contract and exit. The dispersion of productivity across firms is large in magnitude contributing to a high pace of reallocation of workers across firms. Using a decomposition of net job flows into those accounted for by job-to-job flows and those accounted for net flows from nonemployment, we find that much of the overall reallocation of employment from less productive to more productive firms is accounted for by job-to-job flows. The pace at which workers move up the productivity job ladder is highly procyclical. The collapse of the productivity job ladder is consistent with a sullying effect of recessions. In recessions, we find that the reallocation of workers away from less productive firms via nonemployment flows increases. This occurs through a spike in separations to nonemployment along with a decline in hires from nonemployment at low productivity firms. Thus, we also find evidence that this component of reallocation is consistent with a cleansing effect of recessions.

The timing of the cleansing and sullying effects differs across stages of the cycle. The cleansing effect peaks relatively early in a downturn coincident with the relatively early spike in separations. The sullying effect peaks later in a downturn but lingers into the early stages of a recovery when unemployment is falling but remains well above trend.

Our findings are robust to using a direct measure of productivity based on relative differences in revenue per worker across firms within the same industry and an alternative measure of firm performance based on using the AKM firm premium. Since the AKM firm premium abstracts from worker heterogeneity, this robustness suggests our results are not being driven by variation in the patterns of sorting of heterogeneous workers across heterogeneous firms over the cycle. This is not to suggest that the latter is unimportant but rather that there may be additional effects of cleansing and sullying from sorting above and beyond those we have quantified. We recognize that any conclusions about the role of sorting over the cycle for productivity fluctuations are tentative at best. Further theoretical and empirical work is needed in this area.

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Appendix A Assessing Measurement Issues

A.1 Worker Flows

There is a residual term, $\tilde{\epsilon}_t^h$, in equation 2. Figure A.1 plots this residual and illustrates that it is smaller in magnitude than the poaching and nonemployment flows and does not exhibit clear a cyclical pattern. One possible explanation for this residual is that the flows in this section only include cases in which both the origin and destination firms are located in our 28-state sample. In unreported results, we directly measure the out-of-sample worker flows and find that they are not the source of the residual term. To provide evidence that out-of-sample worker flows are not affecting our results, Figure A.1 also plots the poaching and nonemployment flows that include all hires into firms in our sample (including hires from firms located in states outside of our sample) and all separations from firms in our sample (including separations to firms located in states outside of our sample). The patterns are quite similar regardless of whether out-of-sample flows are included, suggesting the migration in and out of our 28-state sample is unlikely to affect our main results.

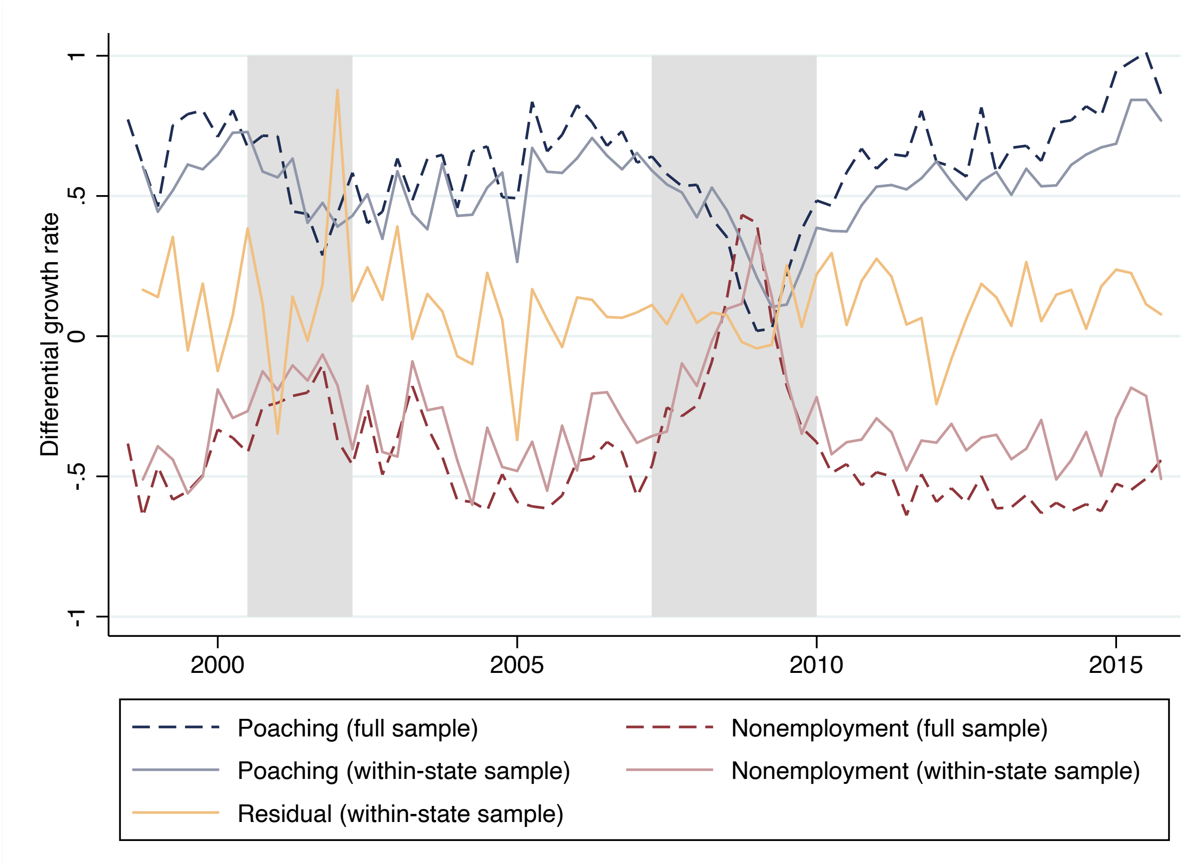
A.2 Productivity

To put our numbers in perspective we compare them to an aggregate measure of productivity growth calculated from the RE-LBD. We calculate aggregate productivity growth by limiting the sample of firms to those that appear in our sample and then calculating the log difference between total revenue per worker within each 4-digit NAICS industry code. Aggregate productivity growth for this purpose is measured as the employment-weighted average of these industry-level growth rates.[35] Figure A.2 compares our measure of productivity growth to other widely used measures from the BLS and the BEA. The measure labeled BLS(industry) is the closest conceptually to our measure. It is an employment-weighted average of industry-level (4-digit NAICS) labor productivity growth rates. The industry-level growth rate is based on the growth rate in what BLS calls sectoral output per worker. Sectoral output is gross output less intrasectoral transactions. At the 4-digit level the adjustment for intrasectoral transctions is modest. The mean of the RE-LBD based measure is 1.3 log points while the mean of the BLS(industry) measure is 1.7 log points. The correlation of these two series is 0.85.

The BLS(sector) and BEA measures are growth rates of value added per worker for the private, non-farm business sector. These measures are distinct conceptually from the RE-LBD and BLS(industry) measures. The latter only capture within-industry contributions to aggregate productivity growth while the value-added measures not only use a conceptually different output measure but also reflect shifts in employment from low- to high-productivity industries. Still these alternative measures exhibit similar patterns to the RE-LBD and BLS(industry) measures. Interestingly, the BLS(sector) average growth rate is 2 log points which is larger than the BLS(industry) measure at 1.7 log points. While appropriate caution is needed to compare these measures given conceptual differences, this pattern is consistent with between industry effects contributing positively to aggregate productivity growth.

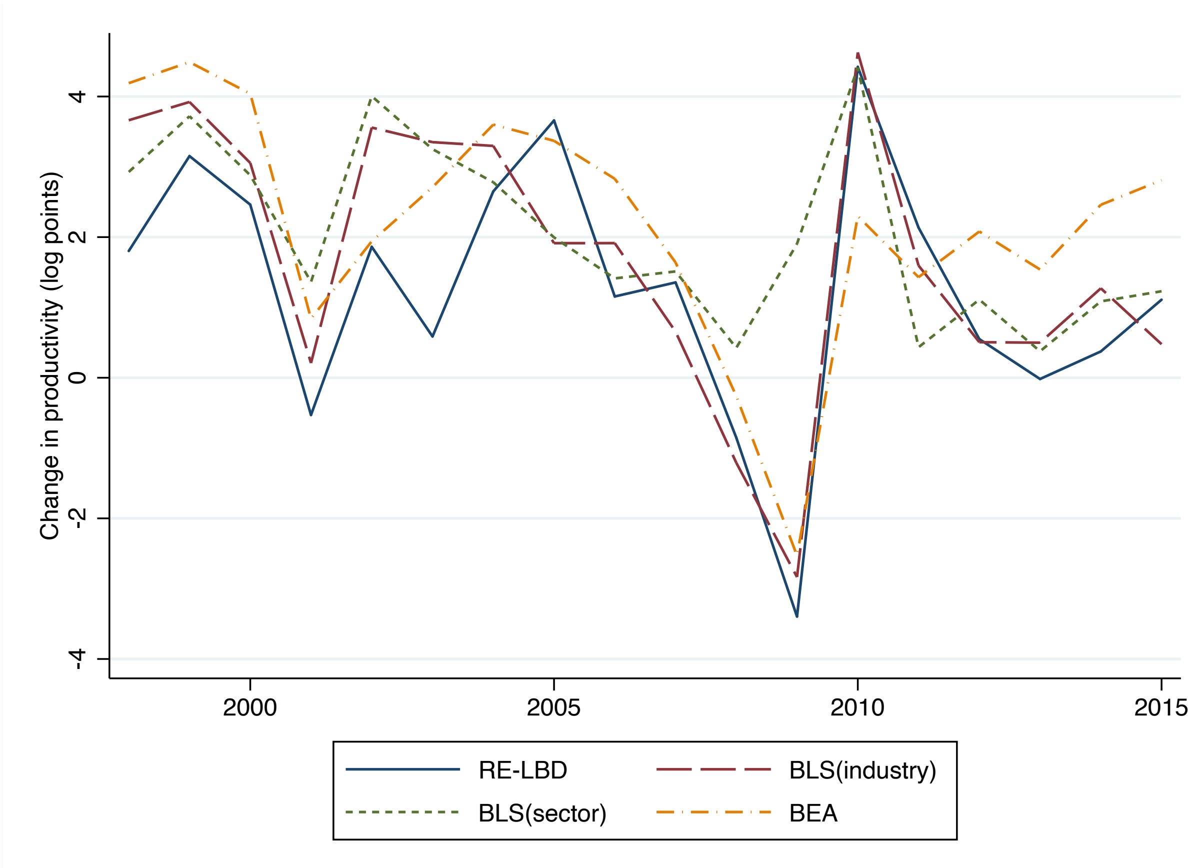
[35] The employment used for weighting is the average of employment in the current and previous year.

Figure A.1: Differential Flows between High and Low Productivity Firms with Residual



Notes: Differential growth rates are the difference in quarterly employment growth rates between high- and low-productivity firms. Results are presented separately for poaching, nonemployment, and residual flows. The poaching and nonemployment flows depicted by the dashed lines are based on the full sample. The poaching and nonemployment flows depicted by the solid lines are based on a sample that is limited to worker flows in which both the origin and destination employers are in one of the 28 states in our sample. The residual growth rate is the difference between the observed changes in the share of employment at high- and low-productivity firms and what is predicted by the poaching and nonemployment flows. Data are seasonally adjusted using X-12.

Figure A.2: Aggregate Productivity Growth from Alternative Sources



Notes: This figure presents annual aggregate productivity growth based on four different sources that include: (1) confidential data from the RE-LBD that characterizes the growth of all firms in our data, (2) publicly available data from the BLS based on industry-level productivity growth, (3) publicly available data from the BLS based on sector-level productivity growth, and (4) publicly available data on industry-level measures of value added from the BEA. To estimate aggregate productivity growth from the RE-LBD, we follow a methodology similar to the BLS and calculate the log difference in total revenue per total number of workers between the current and subsequent year for each industry, then take the employment weighted average across industries.

Figure A.3 compares aggregate productivity growth to the growth attributable to worker reallocation. Data in the RE-LBD are reported at an annual frequency so we sum the quarterly components of productivity growth from our decomposition within each calendar year. Across all years in the sample, average aggregate productivity growth is 1.3 log points per year and the components attributable to poaching and nonemployment flows contribute, on average, 0.4 and -0.3 log points per year, respectively. Thus, at the annual frequency our decomposition captures a quantitatively important aspect of productivity growth. The aggregate series exhibit a relatively larger decline in productivity growth during recessions. For example, between 2007 and 2009 annual productivity growth declined by 4.8 log points. In contrast, the decline in productivity growth attributable to poaching flows can only account for 0.3 log points. However, part of the movements in aggregate productivity reflect measurement error due to cyclical changes in factor utilization.

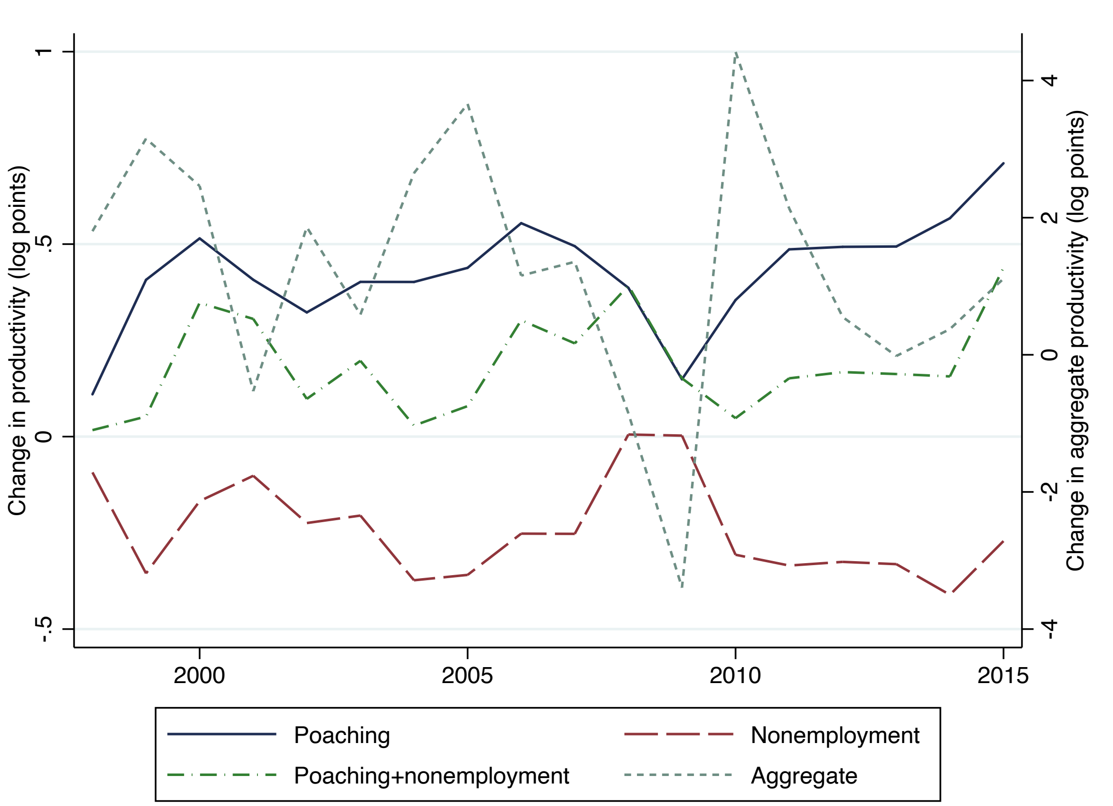
One concern with our measure of productivity is that it does not account for intertemporal variation in factor utilization. During a recession a firm may decide to cut back on production (possibly by reducing workers' hours or worker intensity), which could lead to a decline in log revenue per worker without any real changes in productivity. This issue could affect both our decomposition results and the our aggregate measure of productivity growth.

Intertemporal variation in factor utilization does not appear to meaningfully affect the decomposition results. This is because, to the extent that log revenue per worker is subject to this concern, it affects high- and low-productivity firms to an equal extent. Figure A.4(a) plots, $\tilde{R}^h_{t-1} - \tilde{R}^l_{t-1}$, which is the productivity differential between high- and low-productivity firms. The productivity differential is orders of magnitudes larger than the short-term variation, which may be driven by intertemporal variation in factor utilization. To illustrate that the short-term variation in these differentials does not affect the decomposition exercise, we construct a smoothed series by fitting a linear time trend to the productivity differentials. We then use this smoothed series to implement the productivity growth decomposition. Figure A.4(b) presents the results and shows that the decomposition using the actual and smoothed productivity series yield essentially the same results. To quantify this we regress the component of productivity growth attributable to poaching flows using the observed productivity differentials on the series using the smoothed differentials. The R-squared is 0.99. The analogous R-squared for the nonemployment flows is 0.999.

Variation in factor utilization over the business cycle is a greater issue for our measure of aggregate productivity growth. Fernald (2014) produces a series of growth in business sector TFP that adjusts for factor utilization. Figure A.5(a) presents both the adjusted and unadjusted growth rates from these data. The unadjusted series exhibit a larger decline in TFP during recessions relative to the adjusted series. To get a sense of how sensitive our measure of productivity growth is to changes in factor utilization, we use the difference between the unadjusted and adjusted series from Fernald (2004) to adjust for variation in factor utilization.[36] Figure A.5(b) compares the productivity growth attributable to worker reallocation to the adjusted and unadjusted measures of aggregate productivity growth.

[36]Specifically, we calculate the difference between the adjusted and unadjusted growth rates in 2001 and 2008. We adjust our growth rate by adding these differences to the growth rates in 2001 and 2008. Because our data also exhibit a large decline in 2009, we also add the 2008 difference from the Fernald (2014) series to the 2009 growth rate.

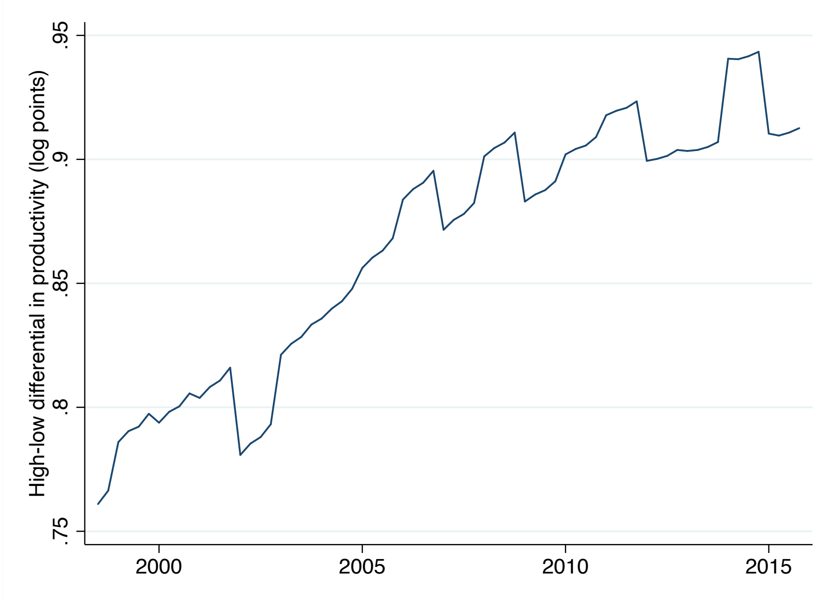
Figure A.3: Annual Productivity Growth from Worker Reallocation



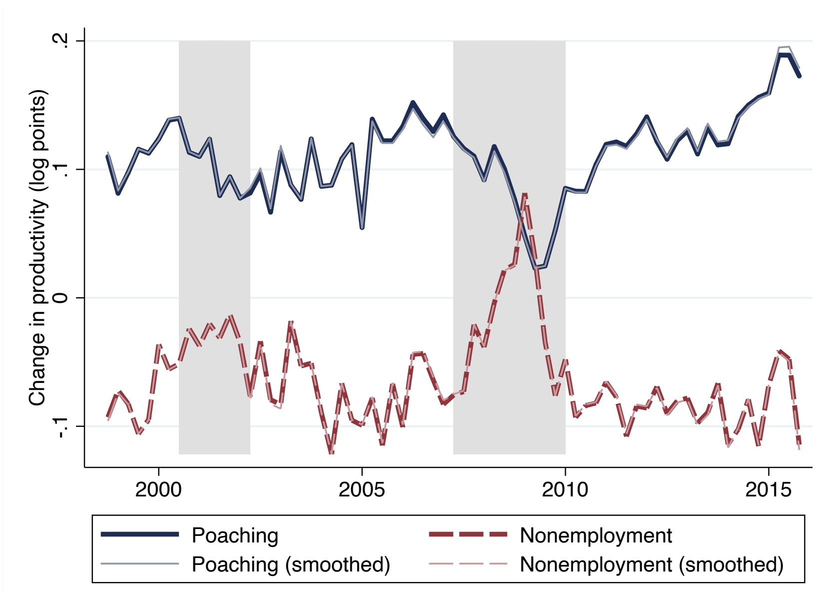
Notes: The figure presents the components of annual productivity growth that are attributable to worker reallocation between high- and low-productivity firms through poaching and nonemployment flows as well as the sum of these two components. Annual productivity growth is the sum of the quarterly growth within a calendar year for these components. The figure also presents a measure of aggregate productivity growth that is calculated from the RE-LBD micro data.

Figure A.4: Decomposition and Intertemporal Variation in Factor Utilization

(a) Productivity Differential



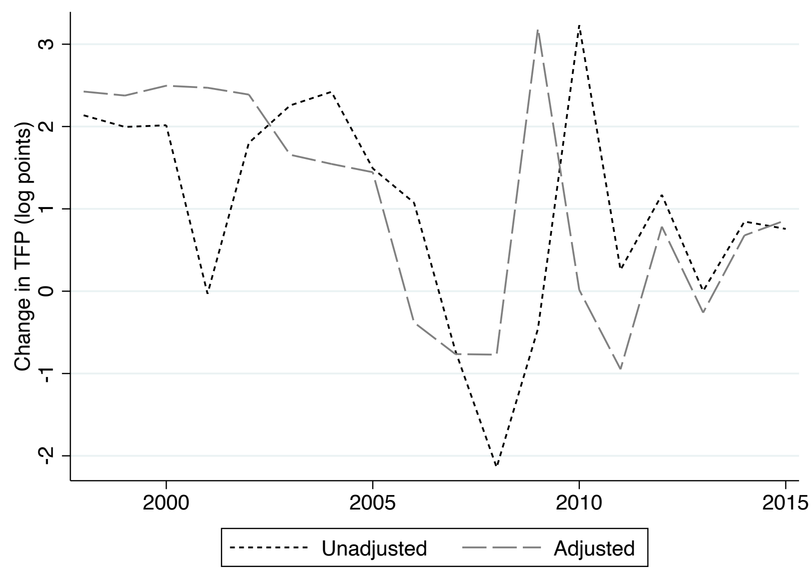
(b) Productivity Decomposition



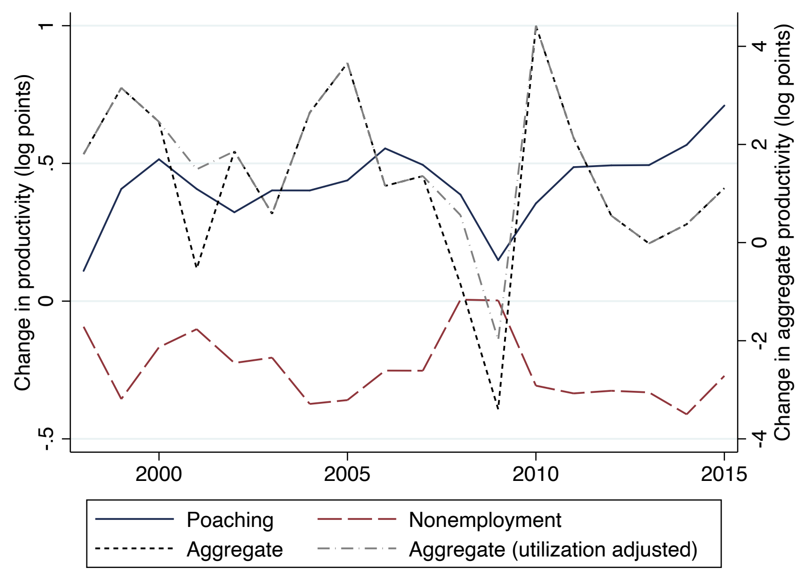
Notes: Panel (a) plots the difference between the average productivity at high- and low-productivity firms. Panel (b) presents the components of productivity growth that attributable to worker reallocation between high- and low-productivity firms through poaching and nonemployment flows. The results in Panel (b) implement the decomposition using both the observed productivity differentials (depicted in Panel (a)) as well as the productivity differentials from a smoothed series generated by fitting the observed productivity differentials with a linear time trend. Data are seasonally adjusted using X-12.

Figure A.5: Aggregate Productivity Growth with Factor Utilization Adjustment

(a) Aggregate Productivity Growth from Fernald (2014)



(b) Productivity Decomposition with Utilization Adjustment



Notes: Panel (a) presents data from Fernald (2014) on the growth in business sector total factor productivity (TFP) as well as a measure that implements an adjustment for variation in factor utilization. Panel (b) presents the annual productivity growth from worker reallocation through poaching and nonemployment flows as well as aggregate productivity growth. In addition, Panel (b) includes a series that adjusts aggregate productivity growth using the difference between the unadjusted and adjusted measures of growth from Fernald (2014).

Appendix B Decomposition Methodology

B.1 Employment

Equation 2 is an exact accounting identity. To see why this equation holds, begin by assuming that there is a closed system in which all changes in employment are accounted for by hires and separations. This assumption implies that,

$$\frac{\Delta E_t^i}{E_{t-1}^i} = \lambda_t^i + \delta_t^i \text{ for } i \in \{h, l\} \tag{B.1}$$

Then we can write,

$$\begin{aligned}
\Delta\theta_t^h &= \frac{E_t^h}{E_t} - \frac{E_{t-1}^h}{E_{t-1}} \\
&= \frac{E_t^h E_{t-1} - E_{t-1}^h E_t}{E_t E_{t-1}} \\
&= \frac{E_{t-1}^l \Delta E_t^h - E_{t-1}^h \Delta E_t^l}{E_t E_{t-1}} \\
&= \Big(\frac{\Delta E_t^h}{E_{t-1}^h} - \frac{\Delta E_t^l}{E_{t-1}^l}\Big)\theta_{t-1}^h \theta_{t-1}^l \Big(\frac{E_{t-1}}{E_t}\Big) \\
&= \big(\lambda_t^h - \lambda_t^l + \delta_t^h - \delta_t^l\big)\theta_{t-1}^h \theta_{t-1}^l \Big(\frac{E_{t-1}}{E_t}\Big) \\
&= \tilde{\lambda}_t^h + \tilde{\delta}_t^h
\end{aligned} \tag{B.2}$$

where

$$\tilde{x}^h = (x^h - x^l)\theta_{t-1}^h \theta_{t-1}^l \Big(\frac{E_{t-1}}{E_t}\Big) \text{ for } x \in \lambda, \delta \tag{B.3}$$

In practice, the system is not closed and hires and separations do not perfectly predict changes in employment. Thus, define the residual term as $\tilde{\epsilon}_t^h = \Delta\theta_t^h - (\tilde{\lambda}_t^h + \tilde{\delta}_t^h)$.

B.2 Productivity

Assumptions A1 and A2 allow us to isolate the component of productivity growth that is attributable to changes in the share of workers at high-productivity firms. First, note that using an accounting identity, we can rewrite the unobserved measure of productivity as,

$$\begin{aligned}
P_t &= \sum_k \theta_t(k) P_t(k) \\
&= \sum_k \theta_t(k)[\theta_t^l(k) P_t^l(k) + \theta_t^h(k) P_t^h(k)]
\end{aligned} \tag{B.4}$$

Then by assumption A1,

$$\begin{aligned} P_t &= \sum_k \theta_t(k)[\theta_t^l(k)R_t^l(k) + \theta_t^h(k)R_t^h(k) + U_t(k)] \\ &= \sum_k \theta_t(k)[\theta_t^l(k)\tilde{R}_t^l(k) + \theta_t^h(k)\tilde{R}_t^h(k) + \bar{P}_t(k)] \\ &= \sum_k [\theta_t(k)\bar{P}_t(k)] + \sum_{i\in\{l,h\}} \left[\sum_k [\theta_t(k)\theta_t^i(k)] \sum_k [\theta_t(k)\tilde{R}_t^i(k)] + \sum_k [cov(\theta_t^i(k), \tilde{R}_t^i(k))]\right] \end{aligned} \tag{B.5}$$

where $cov(\theta_t^i(k), \tilde{R}_t^i(k)) \equiv \sum_k[\theta_t(k)\theta_t^i(k)\tilde{R}_t^i(k)] - \sum_k[\theta_t(k)\theta_t^i(k)]\sum_k[\theta_t(k)\tilde{R}_t^i(k)]$ and $\bar{P}_t(k) \equiv [P_t^l(k) + P_t^h(k)]/2$. Equation B.5 in combination with assumption A2 allows to rewrite productivity growth as,

$$\begin{aligned} \Delta P_t &= \Delta\left(\sum_k [\theta_t(k)\bar{P}_t(k)] + \sum_{i\in\{l,h\}} \left[\sum_k [\theta_t(k)\theta_t^i(k)] \sum_k [\theta_t(k)\tilde{R}_t^i(k)]\right]\right) \\ &= \Delta\left(\sum_k [\theta_t(k)\bar{P}_t(k)] + \sum_{i\in\{l,h\}} \theta_t^i \tilde{R}_t^i\right) \\ &= \sum_{i\in\{l,h\}} \left[\tilde{R}_{t-1}^i \Delta\theta_t^i + \theta_t^i \Delta\tilde{R}_t^i\right] + \Delta\left(\sum_k [\theta_t(k)\bar{P}_t(k)]\right) \\ &= (\tilde{R}_{t-1}^h - \tilde{R}_{t-1}^l)\Delta\theta^h + \theta_t^l \Delta\tilde{R}_t^l + \theta_t^h \Delta\tilde{R}_t^h + \Delta\left(\sum_k [\theta_t(k)\bar{P}_t(k)]\right) \end{aligned} \tag{B.6}$$

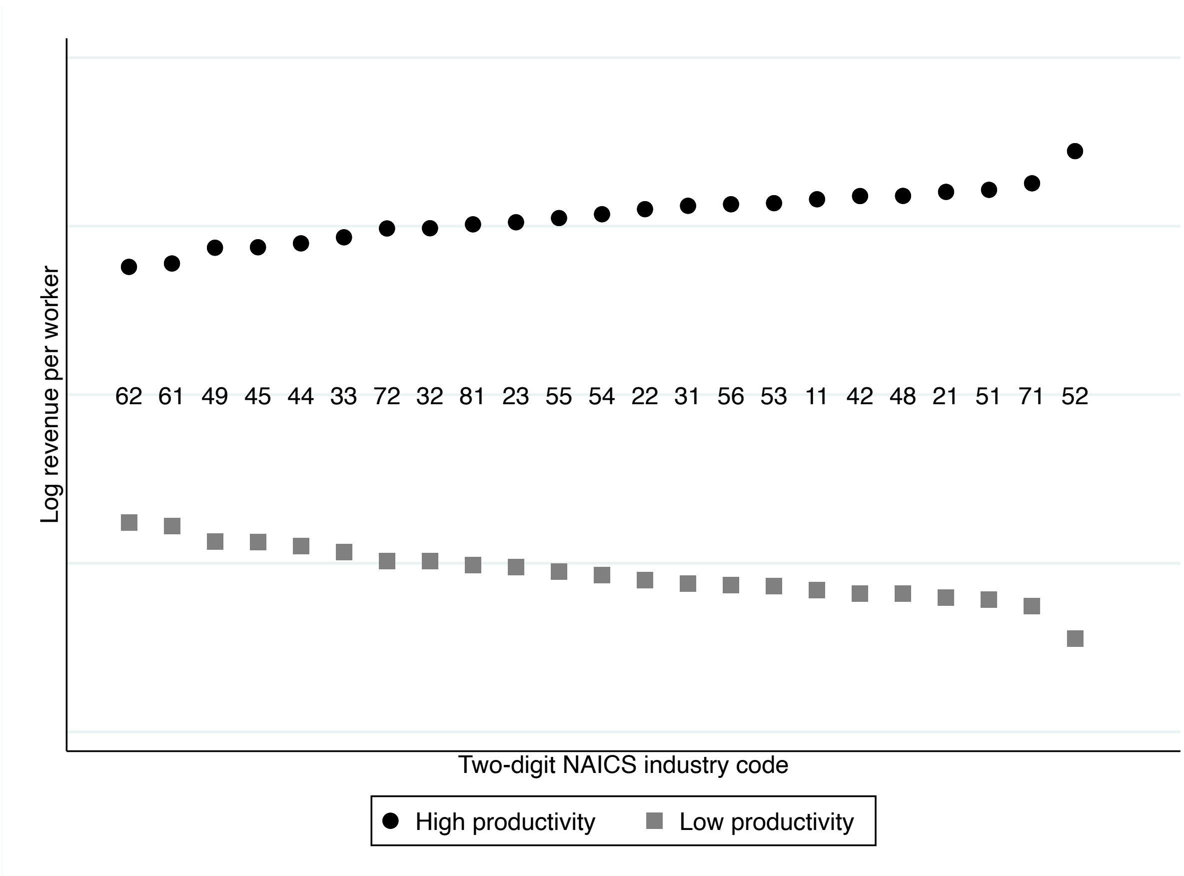
The first term is the component of productivity growth that is attributable to worker reallocation between high- and low-productivity firms.

B.3 Empirical Assessment of Assumptions

Assumption A1 states that log revenue per worker is a valid measure of productivity that is comparable across industries up to an additive constant. Section 2.1 provides some evidence to support this assumption by showing that log revenue per worker deviated from the industry average is predictive of employment growth and survival. To further assess the plausibility of this assumption we plot the average industry-deviated log revenue per worker, $\tilde{R}^i(k)$, for each two-digit NAICS industry code. The results, presented in Figure B.1, illustrate that there are no outliers in terms of the dispersion of log revenue per worker within industries. The industry with the least dispersion in productivity is Health Care and Social Assistance (NAICS=62) and the difference between the average log revenue per work at high- and low-productivity firms is 76 log points. The industry with the most dispersion in log revenue per worker is Finance and Insurance (NAICS=52) and the difference between the average log revenue per work at high- and low-productivity firms is 145 log points. While there are clearly differences in the dispersion of log revenue per worker within different industries, the lack of outliers lend some support to the plausibility of assumption A1.

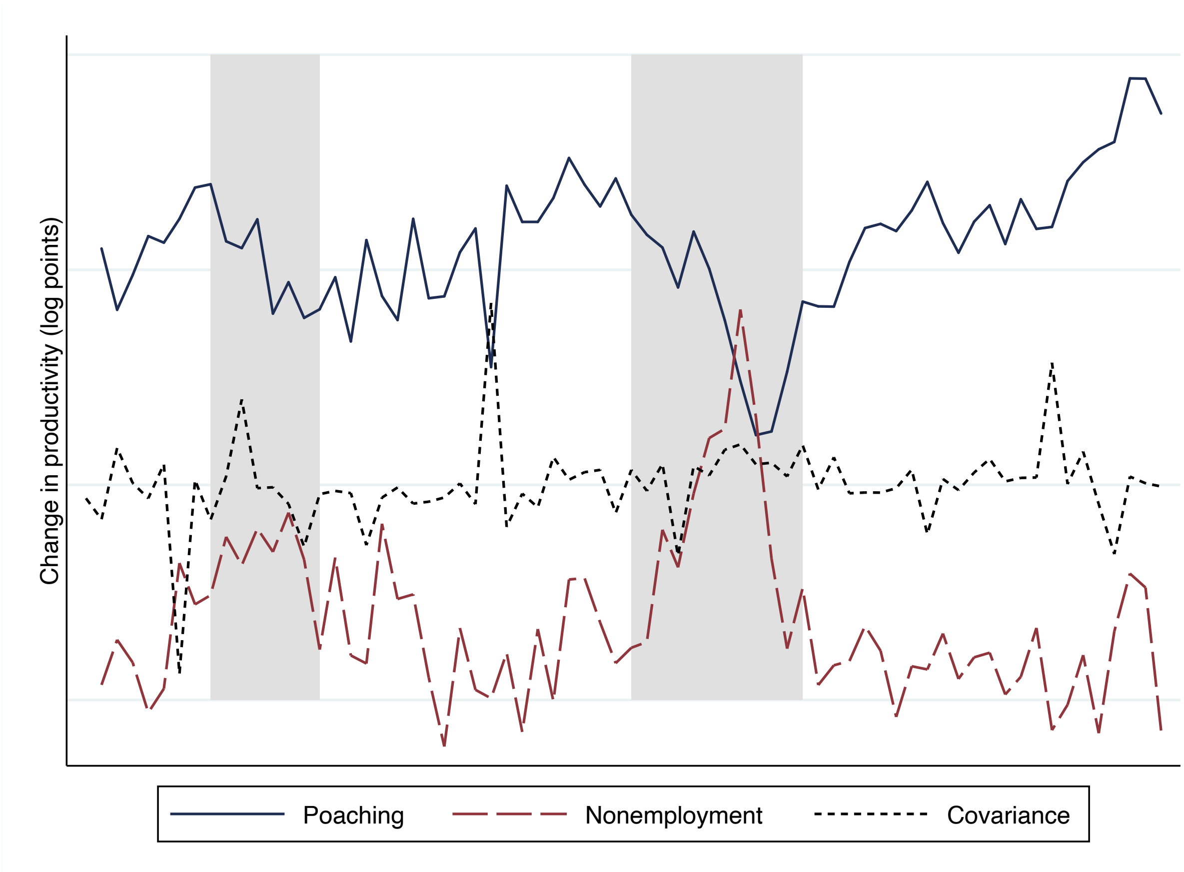
Assumption A2 states that the covariance between the share of employment at high-productivity firms and the dispersion of log revenue per worker does not change over time.

Figure B.1: Log Revenue per Worker Deviated from Industry Average



Notes: This figure presents the average value of log revenue per worker deviated from the average at the four-digit NAICS industry code for each two-digit NAICS industry code.

Figure B.2: Magnitude of Change in Covariance Term



Notes: This figure presents the components of productivity growth that attributable to worker reallocation between high- and low-productivity firms through poaching and nonemployment flows as well as the covariance term, $\Delta\Big(cov\big(\theta^i_t(k), \tilde{R}^i_t(k)\big)\Big)$. Assumption A2 states that the covariance term is zero. This term is numerically equivalent for high- and low-productivity firms. Data are seasonally adjusted using X-12.

This assumption could be violated if industries that experience an increase in productivity growth also experience an increase in the dispersion of productivity across firms. While this is possible, we argue that any violation of this assumption is not quantiatively important. The term $\Delta\Big(cov\big(\theta_t^i(k), \tilde{R}_t^i(k)\big)\Big)$ would show up on the right-hand-side of equation 3 if it were nonzero and we can show that the term is substantially smaller than the components of productivity growth that are attributable to worker reallocation. Specifically, the average value of the absolute value of the productivity growth attributable to worker reallocation through poaching and nonemployment flows is nine and six times larger than the average value of the absolute value of the covariance term, respectively. Figure B.2 makes this same point in more detail by plotting the covariance term as well as the components of worker reallocation through poaching and nonemployment flows over time. Taken together, assumption A2 appears to be a reasonable assumption.